Analyzing The Relationship Between Learning Activity and Student's Performance Using Machine Learning Techniques

Report submitted to the SASTRA Deemed to be University as the requirements for the course

CSE300 – MINI PROJECT

Submitted by

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Mini Project *Viva voce* held on 06/05/24

Examiner 1

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ABBREVATIONS

KNN	K-Nearest Neighbors Algorithm
SVM	Support Vector Machine
ANN	Artificial Neural Network
XGBOOST	Extreme Gradient Boosting
SMOTE	Synthetic Minority Over-Sampling Technique

ABSTRACT

In the present era, various factors visibly affect student academic performance. Recognizing and strategically addressing these factors is important for enhancing overall educational achievements.

In this project, machine learning methodologies such as K-Nearest Neighbors Algorithm (KNN), Support Vector Machine (SVM), Artificial Neural Networks (ANN), and XGBoost are employed on real dataset that has been collected from students which consists the key factors like class attendance, sleep habits, interest on subject, social network usage and participation during lectures etc., are considered for analyzing the major factors that influences the academic outcomes. Hyper parameter tunning has been done using Grid-Search technique to increase the performance of the model. The performances of these methodologies are compared and validated using K-fold cross validation.

Key Words:

Machine Learning, K-Nearest Neighbors Algorithm, Support Vector Machine, Artificial Neural Network, XGBoost, K-fold cross valid, Grid-Search technique.

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CHAPTER 1

SUMMARY OF THE BASE PAPER

Title: An artificial neural network for exploring the relationship between learning activities and students' performance

Journal Name: Science Direct-Decision Analytics Journal

Authors: Kourosh Borhani, Richard T.K.Wong

Year: 2023

1.1 SUMMARY:

- The study's main objective is to examine how various learning activities affect students' academic performance using artificial neural networks. A model of supervised artificial neural networks is created in order to determine which elements have the biggest impact on students' grades.
- Questionnaire design is the techniques used in data collecting to assess the variables affecting student performance.
- To improve the dataset for training, methods including data augmentation and the Synthetic Minority Oversampling Technique (SMOTE) are used.
- The input, hidden, and output layers make up the network architecture, and each layer has a unique activation function that has been selected for best results.
- Based on the elements affecting student performance that have been found, the study attempts to give educators insights to improve their teaching tactics.

1.2 BACK GROUND

Below are some of the key concepts that are useful for the implementation of the project and the reason behind usage of the concepts are described

1.3 DATA PREPROCESSING

1.3.1 SMOTE DATA AUGMENTATION:

The Synthetic Minority Over-sampling Technique is referred to as SMOTE. It is a technique for resolving class imbalance in datasets, particularly in situations involving categorization where one class is noticeably more common than the others. It works by creating new examples for the minority class by finding similar instances and generating new ones along the line connecting them. So, it essentially fills in the gaps between existing minority class samples to balance the dataset, which enhances the model's capacity to learn from minority class samples and produce more precise prediction results.

1.3.2 STANDARD SCALING:

Z-score normalization, sometimes referred to as standard scaling, is a technique for standardizing the dataset's feature range. The data is changed so that its standard deviation is one and its mean is zero. Standard scaling is in especially handy when features have various units or scales. It guarantees that each feature contributes equally to the model's training process by scaling the features to a specified range.

1.3.3 ONE-HOT ENCODING:

One-hot encoding is the process of encoding a categorical variable using a binary (0 or 1) variable for each category.

1.4 MACHINE LEARNING METHODOLOGIES

To determine which model is optimal for analysing student academic achievement, this project makes use of a variety of machine learning techniques. Every approach possesses distinct skills that are appropriate for the analysis.

1.4.1 K-NEAREST NEIGHBORS ALGORITHM

Both regression and classification tasks make use of KNN. Based on the concept of similarity metrics, a data point's class is ascertained by comparing it to the majority class of its k closest neighbours. To put it simply, it uses the classes of the data points that are close by to classify a given data point. The KNN is selected due to its ease of use and efficiency in detecting patterns within the data. It accepts both numerical and categorical data with ease and does not make any strong assumptions about the distribution of the underlying data. Additionally, it fits the project's scope nicely because it is appropriate for small to medium-sized datasets. The following parameters are used to tune the model performance:

1. **NUMBER OF NEIGHBORS (**n_neighbours): The number of neighbours to take into account while making predictions is specified by this parameter. It establishes the number of data points that will affect a particular data point's classification.
2. **WEIGHTS** (weights): The weight function used for prediction is defined by this parameter. It can take on values like "distance," where neighbours that are closer have more effect, or "uniform," where all neighbours have the same weight.
3. **POWER** (p): The Minkowski distance metric's power parameter is represented by the parameter p. It manages the mechanism for calculating distance. It employs the Manhattan distance for p = 1 and the Euclidean distance for p = 2.

1.4.2 SUPPORT VECTOR MACHINE

A supervised learning technique used for both regression and classification applications is SVM. Finding the best hyperplane in high-dimensional feature spaces to divide data points of various classes with the largest margin is its main goal. By projecting input data into a higher-dimensional space, SVM is capable of handling both linear and nonlinear decision boundaries. It is the method of choice, because SVM can manage complex interactions in high-dimensional domains. In comparison to previous algorithms, it is better at capturing nonlinear decision boundaries and less prone to overfitting. When evaluating student performance data, where the relationships may be complex and nonlinear, SVM can nevertheless produce appropriate predictions even in cases where the data cannot be separated linearly. The following parameters are used to tune the model performance:

1. **C:** It manages the trade-off between reducing categorization error and maximizing margin. Although they may cause overfitting, higher values of C give the decision boundary more freedom.
2. **GAMMA:** It refers the impact on the decision boundary of a single training case. Set to 'auto' causes it to adapt automatically depending on the features of the dataset, whereas 'scale' causes it to adapt based on the scale of the dataset. It essentially regulates the decision boundary's flexibility, which has an impact on generalization and model complexity.
3. **KERNEL:** Indicates the kind of kernel that will be applied to the algorithm. It could be sigmoid, polynomial, linear, or the radial basis function (rbf). The model's performance is impacted by the kernel selection, which also shapes the decision boundary.

1.4.3 XGBOOST

The ensemble learning technique known as gradient boosting machines is powerfully implemented by XGBoost, or Extreme Gradient Boosting. In order to create a strong predictive model, it builds a series of decision trees one after the other, correcting the mistakes of the previous one. Scalability, effectiveness, and excellent results in classification and regression problems are the reasons behind the selection of XGBoost, It ensures the robustness of the model by handling big datasets effectively and resisting overfitting.

XGBoost is a valuable tool for examining student performance information and pinpointing critical elements influencing academic results. The following parameters are used to tune the model performance:

1. **NO OF ESTIMATERS:** Number of decision trees or boosting rounds to be constructed, n_estimators. If adjusted appropriately, higher values can enhance model performance but also cause overfitting.
2. **MAX DEPTH:** A tree's maximum depth. It regulates each tree's depth inside the group. Though they may cause overfitting, deeper trees can catch more intricate patterns.
3. **LEARNING RATE:** To avoid overfitting, step size shrinking is applied. It modifies the ensemble's contribution of individual trees, which impacts the model's capacity for generalization.
4. **SUBSAMPLE:** The training instances' subsample ratio. It helps avoid overfitting by regulating the percentage of samples used to train each tree.
5. **COLSAMPLE BYTREE:** The column subsample ratio used to build each tree. It further prevents overfitting by regulating the percentage of characteristics used in each tree's training.
6. **GAMMA**: The lowest loss reduction needed to split a tree's leaf node farther. By removing trees that don't significantly increase model performance, it adds regularization.

1.4.1 ARTIFICIAL NEURAL NETWORK

Artificial Neural Networks (ANNs) are computer models inspired by the way neurons work in the human brain. An input layer receives data, one or more hidden layers process it, and an output layer generates predictions. They are made up of interconnected nodes, or neurons, arranged in layers. An artificial neural network (ANN) can recognize complex patterns and relationships in data by iteratively training them by changing the weights of the connections between their neurons. The reason ANN is used is because it may identify intricate, nonlinear relationships in data that conventional linear models could miss. Its model design is highly versatile, enabling customisation dependent on the type of data and the problem at hand. It can handle huge and complex datasets. The following parameters are used to tune the model performance:

1. **EPOCHS**: The quantity of times the neural network trains by passing the complete dataset both forward and backward. While more epochs can enhance model performance, an excessive number of epochs can cause overfitting.
2. **LAYER COMBINATIONS**: The arrangement of each layer's neurons and hidden layers. The ability of the model to learn intricate patterns can be impacted by various layer and neuron combinations.
3. **DROPOUT RATES**: In order to keep neural networks from overfitting, dropout is a regularization approach. During training, it arbitrarily turns off a portion of neurons, causing the network to pick up duplicate data representations. The percentage of neurons that are dropped throughout each training cycle is determined by dropout rates

1.5 HYPER PARAMETER TUNING

A crucial stage in maximizing the performance of machine learning models is hyperparameter tuning. Hyperparameters are configurations that regulate how the models learn. The model's ability to learn from the data can be greatly impacted by tuning these hyperparameters.

Grid-Search is the technique is used for fine-tuning hyperparameters in machine learning models. The main idea is to create a grid of hyperparameter values and then thoroughly investigate every possible combination to find the set that maximizes the performance of the model. By adjusting the parameters that are not explicitly learned during training, this technique is used to improve the model's predictive power and capacity to generalize to new data.

1.6 K-FOLD CROSS VALIDATION

The K-Fold Cross Validation technique divides the dataset into k folds, or equal-sized sections, for the purpose of evaluating machine learning models. Using a separate fold as the validation set and the remaining folds as the training set, the model is trained k times. This makes it easier to evaluate the model's performance in-depth when it is tested using various data subsets. By using this method, the likelihood of overfitting—a situation in which a model performs exceptionally well on training data but poorly on fresh data—is decreased and it is ensured that the model can generalize well to new and unseen data.

1.7 PROBLEM DEFINITION

In higher education, there exists a growing disconnect between students and lecturers due to differing expectations and increasing academic pressures. As most higher education teaching approaches relay on the self-discipline of the students.Traditional teaching evaluation methods often lack the ability to find student engagement and ability to understand the impact of various learning activities on academic performance. With the rise of deep learning techniques, there emerges an opportunity to address these challenges more effectively. It also offers advanced capabilities in analyzing complex factors that affect the student performance. which can be particularly beneficial in understanding the relationships between learning activities and academic performance. This advancement holds promise for bridging the gap between student expectations and academic outcomes in higher education, ultimately fostering a more connected and supportive learning environment.

1.8 PROPOSED METHODOLOGY:

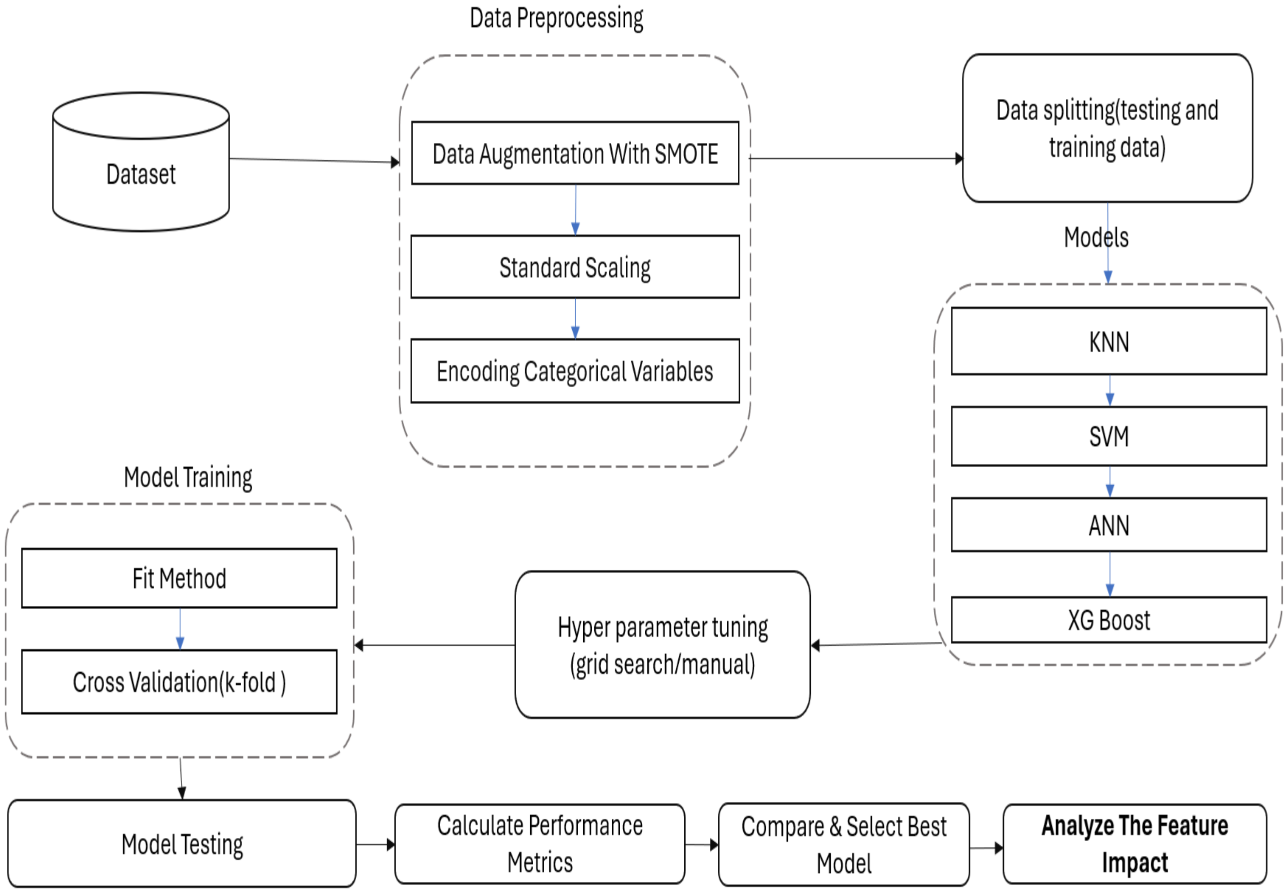

Fig 1.1 Proposed methodology

DATASET

The dataset used for the project is the real dataset collected through a survey form. It has 790 samples with 24 attributes along with target class (GRADE).

1.9 TECHNOLOGIES USED:

To implement this project, several technologies and libraries were utilized, each serving a specific purpose:

TensorFlow and Keras: TensorFlow, serving as the foundation for machine learning tasks, partners with Keras, a user-friendly interface built upon TensorFlow, streamlining neural networkdevelopment.

NumPy: Empowers efficient mathematical operations and data manipulation, offering supportfor essential data structures like arrays and matrices, pivotal for neural network computations.

Scikit-learn: Furnishes a rich toolkit for machine learning endeavors, encompassing preprocessing utilities, model training algorithms, and performance evaluation metrics, enrichingproject efficacy.

Matplotlib: Matplotlib is an extensive Python plotting package. It offers an interface for making a variety of static, interactive, and animated visualizations that is similar to MATLAB.

Pandas: For Python, Pandas is a robust data manipulation and analysis library. It offers functions and data structures for effectively manipulating and analyzing structured data, especially when it comes to tabular data.

The machine used for this project is Visual Studio and laptop with following specifications.

- Processor: Intel i3 Core -2100CPU @ 3.10GHz
- Random Access Memory (RAM) : 8GB
- Operating System : Windows 11 64-bit

CHAPTER 2

MERITS AND DEMERITS OF BASE PAPER

2.1 LITERATURE SURVEY:

1. TITLE : **Prediction of Students' Performance in Students' Marks using Supervised Learning**
   AUTHOR : Namrata Vij, Shashi Ranjan
   YEAR : 2023
   JOURNAL : IEEE

The study uses linear regression, which predicts student performance with 95% accuracy using characteristics such as study hours and prior grades. However, in order to achieve better results, it is advised to investigate alternatives such ensemble methods or support vector machines. These methods have the advantage of not being as sensitive to outliers, overfitting.

2. TITLE : **Will the Student Get an A Grade? Machine Learning-based Student Performance Prediction in Campus**
   AUTHOR : Ali Alnoman
   YEAR : 2023
   JOURNAL : IEEE

In order to predict student performance, the study explored a number of machine learning models. Bagged trees and K-nearest neighbours had the highest accuracy (99% and 98.1%, respectively). Training was conducted using attributes such as high school grade, course midterm grade, and absence rate. Sophisticated models, like bagged trees, can make accurate predictions by combining many simpler models, but they often sacrifice easy interpretation because of their complexity. In order to prevent overfitting and guarantee accurate student performance prediction, it is essential to strike a balance between interpretability, generalization, and model complexity.

3. TITLE : **Prediction on Impact of Electronic Gadgets in Students Life using Machine Learning**

AUTHOR : Saraswathi S, Deva K, Dharshini S,Kavina S

YEAR : 2023

JOURNAL : IEEE

For the purpose of assisting educational stakeholders in making well-informed decisions, machine learning models such as Logistic Regression, K-NN, SVM, Random Forest, and Decision Tree have demonstrated exceptional accuracy in forecasting student performance and measuring the influence of gadgets. These models support evidence-based teaching practices by encouraging data-driven decision-making. The size of attribute considered in the study decrease the reliability of the study. And the problems including overfitting, reliance on data quality, interpretability problems, biases, scalability and constraints highlight the necessity of cautious application and continuous assessment.

4. TITLE : **Determining factors that affect student performance using various machine learning methods**

AUTHOR : Nicholas Robert Beckham, Limas Jaya Akeh, Giodio Nathanael Pratam Mitaart

YEAR : 2022

JOURNAL : Science-direct Procedia computer science

Based on 33 variables, the study used Random Forest, Decision Tree, and Multi-Layer Perceptron (MLP) models to predict student success. Good prediction accuracy was demonstrated by the MLP's RMSE of 4.32, Decision Tree's RMSE of 5.69, and Random Forest's RMSE of 4.52. Using a combination of categorical and numerical factors, attributes like school, age, family support, study time, health, past failures, and absences were taken into account. Among the benefits were precise forecasting made possible by the identification of pertinent attributes, which provided information about things like parental education and prior failures. However, due to a small dataset and possible model complexity concerns in addressing complicated variable interactions, limitations were raised regarding the representativeness of the data.

2.2 MERITS:

- It addresses the application of supervised data analysis techniques to find influential learning elements towards students’ academic performance.
- Uses the SMOTE augmentation method to handle the minimum data size
- Explores the variables that impact student performance in and out of the classroom, stressing the importance of student attendance, workload, and other relevant variables.
- Questionnaires maintain anonymity, participants have the option to participate in the study without the researchers’ knowledge in the survey thus provide proper comfort to the participants
- Addresses questionnaire design issues, highlighting the significance of proper data collection.
- Through analysis, the research attempts to break the knowledge gaps by offering teachers insights on how to enhance their student’s performance based on factors that have been found to affect students' performance.

2.3 DEMERITS

Limited Model Comparison: Although the paper talks about how well different AI models anticipate students' challenges and performance, it does not provide a thorough comparison of how each model performs when dealing with intricate educational datasets or particular scenarios.

Data gathering Issues: limited data size have been used so that the model can’t generalizes well to unseen data

Limited Attribute selection: Restricting the scope and depth of the analysis by concentrating on just a few key attributes may cause it to miss other significant elements that may have an impact on students' performance. A more thorough investigation of a larger range of characteristics might offer a more comprehensive comprehension of the intricate connections between different elements and student outcomes.

CHAPTER 3

SOURCE CODE

3.1 DATA PREPROCESSING:

```
from sklearn.preprocessing import MinMaxScaler
from imblearn.over_sampling import SMOTE
import pandas as pd
from sklearn.preprocessing import LabelEncoder
# Load your dataset
data = pd.read_csv('realdata.csv')

# Separate features and target variable
X = data.drop('Grade', axis=1)
#X = X.drop('Timestamp',axis=1)
y = data['Grade']


# Step 2: Data Augmentation with SMOTE
smote = SMOTE()
X_resampled, y_resampled = smote.fit_resample(X, y)

# Convert back to DataFrame
X_resampled_df = pd.DataFrame(X_resampled, columns=X.columns)
y_resampled_df  = pd.Series(y_resampled, name='Grade')

# Concatenate features and target variable
augmented_data = pd.concat([X_resampled_df, y_resampled_df], axis=1)

# Save augmented dataset to a new CSV file
augmented_data.to_csv('augmented_dataset.csv', index=False)
```

```
# Load your dataset
data = pd.read_csv('augmented_dataset.csv')

X = data.drop('Grade', axis=1)  # Features
y = data['Grade']

# Splitting the data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=seed_value)

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

3.2 KNN MODEL TRAINING AND VALIDATION:

```
# Define the parameter grid
param_grid = {
    'n_neighbors': [20,22],  # Number of neighbors
    'weights': ['uniform', 'distance'],  # Weighting method
    'p': [1, 2]  # Power parameter for Minkowski distance (1: Manhattan, 2: Euclidean)
}

# Initialize the KNN classifier
knn = KNeighborsClassifier()

# Initialize GridSearchCV
grid_search = GridSearchCV(knn, param_grid, cv=5, scoring='accuracy', verbose=1)

# Perform grid search
grid_search.fit(X_train_scaled, y_train)

# Get the best parameters and best score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

print("Best Parameters:", best_params)
print("Best Score:", best_score)


# Get the best model
best_model = grid_search.best_estimator_
```

3.3 SVM MODEL TRAINING AND VALIDATION:

```
# Set up the parameter grid for grid search
param_grid = {
    'C': [0.1,0.5, 1,1.5],
    'gamma': ['scale', 'auto'],
    'kernel': ['linear','rbf']
}

# Initialize SVM classifier
svm_classifier = SVC()

# Perform grid search with cross-validation
grid_search = GridSearchCV(estimator=svm_classifier, param_grid=param_grid, cv=5, scoring='accuracy')
grid_search.fit(X_train_scaled, y_train)

# Get the best parameters and best score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

print("Best Parameters:", best_params)
print("Best Score:", best_score)
# Use the best model for prediction
best_model = grid_search.best_estimator_
```

3.4 XGBOOST MODEL TRAINING AND VALIDATION:

```
# Perform manual parameter tuning and cross-validation
for n_estimators in params['n_estimators']:
    for max_depth in params['max_depth']:
        for learning_rate in params['learning_rate']:
            for subsample in params['subsample']:
                for colsample_bytree in params['colsample_bytree']:
                    for gamma in params['gamma']:

                            print(f"Evaluating model with n_estimators={n_estimators}, max_depth={max_depth}, learning_rate={learning_rate},subsample

                            accuracy_values = []
                            for train_index, val_index in kfold.split(X_train_scaled):
                                X_train_fold, X_val_fold = X_train_scaled[train_index], X_train_scaled[val_index]
                                y_train_fold, y_val_fold = y_train.iloc[train_index], y_train.iloc[val_index]

                                # Create the XGBoost model
                                model = XGBClassifier(n_estimators=n_estimators, max_depth=max_depth, learning_rate=learning_rate,
                                                      subsample=subsample, colsample_bytree=colsample_bytree)

                                # Fit the model
                                model.fit(X_train_fold, y_train_fold)

                                # Evaluate the model on validation set
                                y_pred = model.predict(X_val_fold)
                                accuracy = accuracy_score(y_val_fold, y_pred)
                                accuracy_values.append(accuracy)

                            mean_accuracy = np.mean(accuracy_values)
                            print(f"Mean Accuracy: {mean_accuracy}")

                            # Update best model if the current model is better
                            if mean_accuracy > best_accuracy:
                                best_accuracy = mean_accuracy
                                best_model = model
                                best_parameters = {'n_estimators': n_estimators, 'max_depth': max_depth, 'learning_rate': learning_rate,
                                                   'subsample': subsample, 'colsample_bytree': colsample_bytree}
```

```
# Define hyperparameters for manual tuning
params = {
      'n_estimators': [100, 200],#100
      'max_depth': [3, 5], #3
      'learning_rate': [0.1, 0.3],#0.1
      'subsample': [0.8, 1.0], #1.0
      'colsample_bytree': [0.8, 1.0], #1.0
      'gamma': [0, 0.1],#0,#0.2
      'reg_alpha': [0, 0.001],#0,#0.0.1
      'reg_lambda': [0, 0.001],#1.0,#0.0.1
}

best_accuracy = 0
best_model = None
best_parameters = None

# Define KFold cross-validation
kfold = KFold(n_splits=5, shuffle=True,random_state=42)
```

3.5 ANN MODEL TRAINING AND VALIDATION:

```
# Define the model creation function
def create_model(layers=[128, 64, 32], dropout_rate=0.5):
    model = tf.keras.models.Sequential()
    model.add(tf.keras.layers.Dense(layers[0], activation='relu', input_shape=(23,)))
    model.add(tf.keras.layers.Dropout(dropout_rate))
    for units in layers[1:]:
        model.add(tf.keras.layers.Dense(units, activation='relu'))
        model.add(tf.keras.layers.Dropout(dropout_rate))
    model.add(tf.keras.layers.Dense(4, activation='softmax'))
    model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
    return model
```

```
epochs_list =[60,70]
layer_combinations =[[64,128],[512, 256, 128, 64],[64,64]]
dropout_rates = [0.3,0.5]
best_accuracy = 0
best_model = None
best_parameters = None
# Define KFold cross-validation
kfold = KFold(n_splits=5, shuffle=True, random_state=seed_value)
# Perform manual parameter tuning and cross-validation
for epochs in epochs_list:
    for layers in layer_combinations:
        for dropout_rate in dropout_rates:
            print(f"Evaluating model with epochs={epochs}, layers={layers}, dropout_rate={dropout_rate}")
            accuracy_values = []
            for train_index, val_index in kfold.split(X_train_scaled):
                X_train_fold, X_val_fold = X_train_scaled[train_index], X_train_scaled[val_index]
                y_train_fold, y_val_fold = y_train_encoded[train_index], y_train_encoded[val_index]
                # Create the model
                model = create_model(layers=layers, dropout_rate=dropout_rate)
                # Fit the model
                history = model.fit(X_train_scaled, y_train_encoded,
                                epochs=epochs,
                                validation_data=(X_val_fold, y_val_fold),verbose=0 )
                # Evaluate the model on validation set
                _, accuracy = model.evaluate(X_val_fold, y_val_fold, verbose=0)
                accuracy_values.append(accuracy)

            mean_accuracy = np.mean(accuracy_values)
            print(f"Mean Accuracy: {mean_accuracy}")

            # Update best model if the current model is better
            if mean_accuracy > best_accuracy:
                best_accuracy = mean_accuracy
                best_model=model
                best_history=history

                best_parameters = {'epochs': epochs, 'layers': layers, 'dropout_rate': dropout_rate}
```

3.6 ERROR IMPACT CALCULATION

```
# Calculate the baseline error for the specified target value
baseline_predictions = loaded_model.predict(X_test_scaled)
baseline_error = mean_squared_error(y_test_encoded[:, target_value], baseline_predictions[:, target_value])

# Calculate the impact of each feature on error for the specified target value
feature_errors = {}
for feature in X.columns:
    # Perturb the feature by adding random noise
    X_test_perturbed = X_test_scaled.copy()
    perturbation = np.random.normal(loc=0.0, scale=0.1, size=X_test_perturbed.shape[0])  # Adjust the scale as needed
    feature_index = X.columns.get_loc(feature)
    X_test_perturbed[:, feature_index] += perturbation

    # Calculate the error with the perturbed feature for the specified target value
    perturbed_predictions = loaded_model.predict(X_test_perturbed)
    perturbed_error = mean_squared_error(y_test_encoded[:, target_value], perturbed_predictions[:, target_value])

    # Store the difference in error
    feature_errors[feature] = perturbed_error - baseline_error

# Sort the features by their impact on error
sorted_features = sorted(feature_errors.items(), key=lambda x: x[1], reverse=True)
feature_mean_values={}
feature_median_values={}
# Print the impact of each feature on error
for feature, error_impact in sorted_features:
    target_value_data =data[(data['Grade']-1)== target_value]
    mean_value = np.mean(target_value_data[feature])
    feature_mean_values[feature] = mean_value
    median_value = np.median(target_value_data[feature])
    feature_median_values[feature] = median_value
    #print(f"Feature '{feature}' - Mean Value: {mean_value:.4f}, Median value: {median_value} ,Error Impact: {error_impact:.6f}")
    print(f"{feature}")
```

CHAPTER 4

SNAPSHOTS

4.1 VALIDATION AND TESTING ACCURACY :

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits
Best Parameters: {'n_neighbors': 22, 'p': 1, 'weights': 'distance'}
Best Score: 0.8722087132725431

['knn_model.joblib']
```

```
Test Accuracy: 0.9147727272727273
Precision: 0.914073745440205
Recall: 0.9125132555673383
f1score: 0.9132676858714409
```

Fig 4.1 KNN testing and training accuracy

```
Best Parameters: {'C': 1.5, 'gamma': 'auto', 'kernel': 'rbf'}
Best Score: 0.8509017223910842

['svm_model.joblib']
```

```
Test Accuracy: 0.9261363636363636
Precision: 0.9333841688338036
Recall: 0.9220572640509014
```

Fig 4.2 SVM testing and training accuracy

```
Evaluating model with n_estimators=100, max_depth=3, learning_rate=0.1,subsample=1.0, colsample_bytree=0.8,gamma=0
Mean Accuracy: 0.8437993920972644
Evaluating model with n_estimators=100, max_depth=3, learning_rate=0.1,subsample=1.0, colsample_bytree=0.8,gamma=0.1
Mean Accuracy: 0.8437993920972644
Evaluating model with n_estimators=100, max_depth=3, learning_rate=0.1,subsample=1.0, colsample_bytree=1.0,gamma=0
Mean Accuracy: 0.8423809523809525
Evaluating model with n_estimators=100, max_depth=3, learning_rate=0.1,subsample=1.0, colsample_bytree=1.0,gamma=0.1
Mean Accuracy: 0.8423809523809525
Evaluating model with n_estimators=100, max_depth=3, learning_rate=0.3,subsample=0.8, colsample_bytree=0.8,gamma=0
Mean Accuracy: 0.9020466058763932
Evaluating model with n_estimators=100, max_depth=3, learning_rate=0.3,subsample=0.8, colsample_bytree=0.8,gamma=0.1
Mean Accuracy: 0.9020466058763932
Evaluating model with n_estimators=100, max_depth=3, learning_rate=0.3,subsample=0.8, colsample_bytree=1.0,gamma=0
Mean Accuracy: 0.8992097264437688
Evaluating model with n_estimators=100, max_depth=3, learning_rate=0.3,subsample=0.8, colsample_bytree=1.0,gamma=0.1
Mean Accuracy: 0.8992097264437688
Evaluating model with n_estimators=100, max_depth=3, learning_rate=0.3,subsample=1.0, colsample_bytree=0.8,gamma=0
...
Evaluating model with n_estimators=200, max_depth=5, learning_rate=0.3,subsample=1.0, colsample_bytree=1.0,gamma=0.1
Mean Accuracy: 0.8949341438703142
Best Parameters: {'n_estimators': 200, 'max_depth': 5, 'learning_rate': 0.3, 'subsample': 0.8, 'colsample_bytree': 0.8}
Best Accuracy: 0.9105471124620061
```

```
Best Parameters: {'n_estimators': 200, 'max_depth': 5, 'learning_rate': 0.3, 'subsample': 0.8, 'colsample_bytree': 0.8}
Test Accuracy: 0.9090909090909091
Precision: 0.9106377483734834
Recall: 0.9090909090909091
```

Fig 4.3 XGBOOST testing and training accuracy

```
Mean Accuracy: 0.9829787373542785
Evaluating model with epochs=60, layers=[64, 128], dropout_rate=0.5
Mean Accuracy: 0.9176393151283264
Evaluating model with epochs=60, layers=[512, 256, 128, 64], dropout_rate=0.3
Mean Accuracy: 1.0
Evaluating model with epochs=60, layers=[512, 256, 128, 64], dropout_rate=0.5
Mean Accuracy: 0.9872340440750123
Evaluating model with epochs=60, layers=[64, 64], dropout_rate=0.3
Mean Accuracy: 0.9730395197868347
Evaluating model with epochs=60, layers=[64, 64], dropout_rate=0.5
Mean Accuracy: 0.90626140832901
Evaluating model with epochs=70, layers=[64, 128], dropout_rate=0.3
Mean Accuracy: 0.9943262457847595
Evaluating model with epochs=70, layers=[64, 128], dropout_rate=0.5
Mean Accuracy: 0.9417933225631714
Evaluating model with epochs=70, layers=[512, 256, 128, 64], dropout_rate=0.3
Mean Accuracy: 1.0
Evaluating model with epochs=70, layers=[512, 256, 128, 64], dropout_rate=0.5
Mean Accuracy: 0.9858156085014343
Evaluating model with epochs=70, layers=[64, 64], dropout_rate=0.3
Mean Accuracy: 0.9872239112854004
Evaluating model with epochs=70, layers=[64, 64], dropout_rate=0.5
Mean Accuracy: 0.916200602054596
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step
Best Parameters: {'epochs': 60, 'layers': [512, 256, 128, 64], 'dropout_rate': 0.3}
Test Accuracy: 0.9431818181818182
Precision: 0.949530349391589
Recall: 0.9390243902439024
F1 score: 0.9388565169936527
```

Fig 4.4 ANN testing and training accuracy

4.2 ACCURACY CAMPARISON GRAPH OF ALL MODEL:

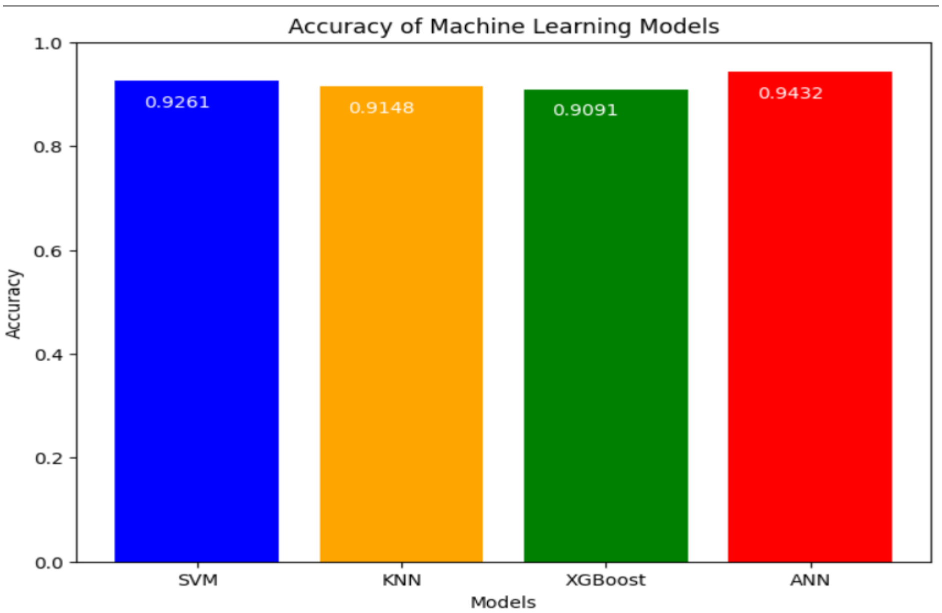

Fig 4.5 Comparison graph for all model

4.3 GRAPH OF ACCURACY AND LOSS OF ANN MODEL:

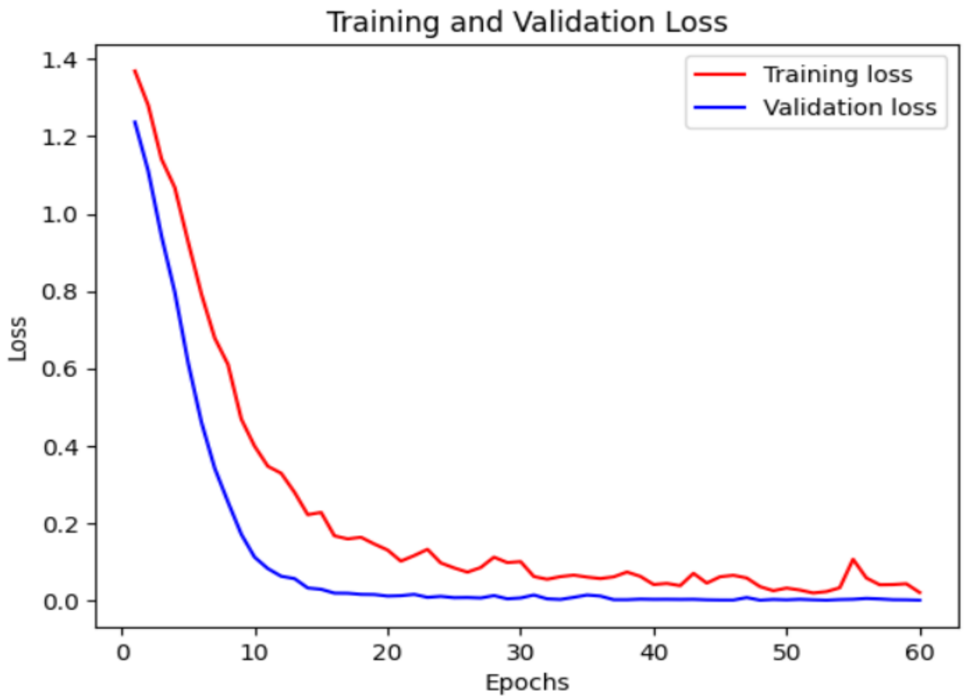

Fig 4.6 Training and validation loss graph

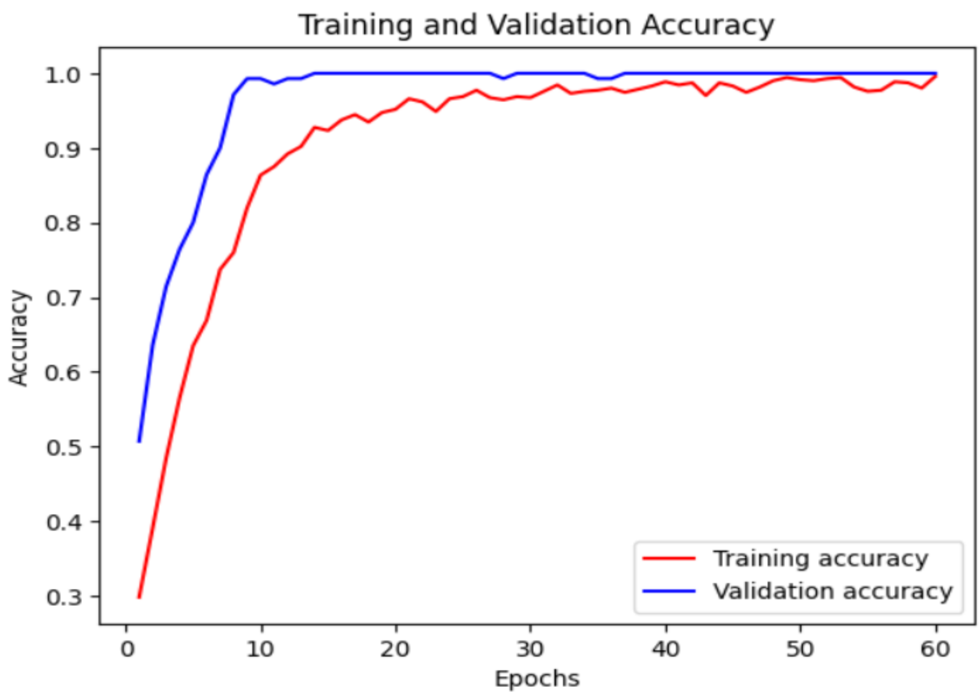

Fig 4.7 Training and validation accuracy graph

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1 RESULTS:

TARGET 1			
LEARNING ACTIVITIES	**MEAN VALUE**	**MEDIAN VALUE**	**ERROR IMPACT**
Reading Textbooks	3.0455	3.0	0.001158
Studying Material Before Class	42.4000	41.5	0.000890
No Of Subjects	2.8545	2.0	0.000733
Interest On Subject	3.0273	3.0	0.000469
Class Discussions	54.5727	58.0	0.000391
Projects	2.4000	2.0	0.000379
Sleep Affecting Class	21.4045	10.0	0.000308
Asking Question In Class	2.3000	1.0	0.000298
Workshops	3.5682	3.0	0.000271
Taking Notes	2.9636	2.0	0.000271
Health Issue	30.6273	30.0	0.000150
Stress	3.8909	4.0	0.000141
Seeking Clarity	2.2727	2.0	0.000133
Reviewing Previous Paper	42.1455	40.0	0.000098
Class Skipped	3.4909	3.0	-0.000007
Completing Assignments	25.9000	18.5	-0.000073
Procrastination	3.2273	3.0	-0.000108
Lack Of Self Discipline	40.5182	41.0	-0.000117
Self Directed Study	5.9364	6.0	-0.000117
Seeking Feedback	3.0500	3.0	-0.000150
Peer Disturbance	35.3455	30.0	-0.000163
Social Media	2.1409	2.0	-0.000269
Over Reliance On Memorization	3.7273	3.0	-0.000402

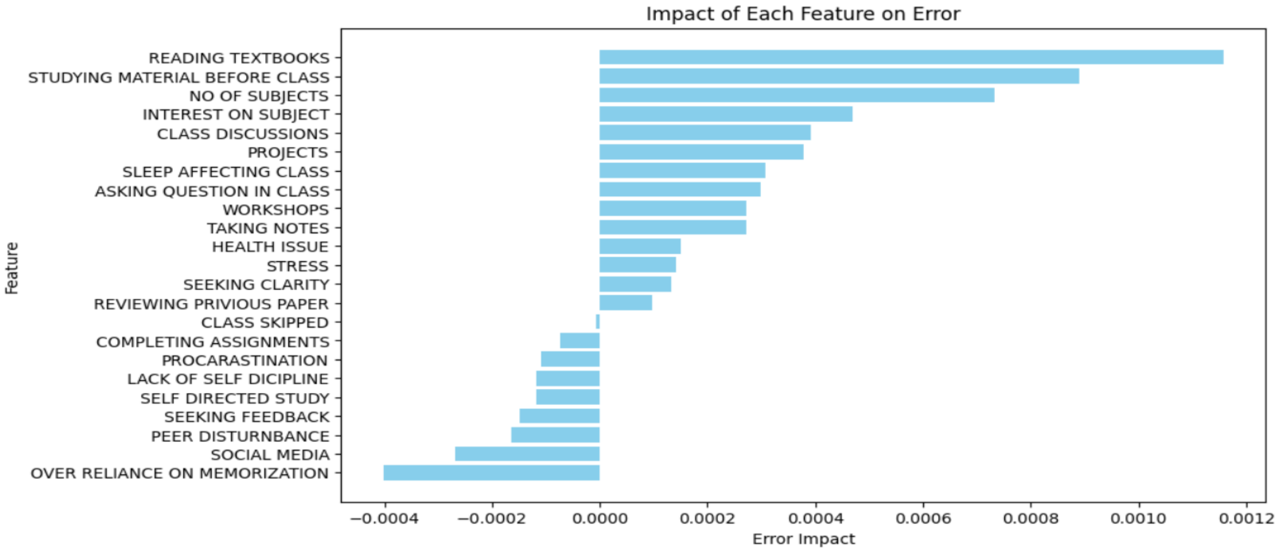

Fig 5.1 Impact of each feature on error for grade:1

TARGET 2			
LEARNING ACTIVITIES	**MEAN VALUE**	**MEDIAN VALUE**	**ERROR IMPACT**
Reading Textbooks	2.7455	2.0	0.001180
Studying Material Before Class	48.5227	50.0	0.000860
Interest On Subject	2.1409	2.0	0.000455
Projects	2.1636	2.0	0.000409
Asking Question In Class	1.8545	1.0	0.000310
Workshops	2.8364	2.0	0.000228
Stress	4.6955	4.0	0.000179
Seeking Clarity	2.2091	2.0	0.000144
Health Issue	23.8273	12.5	0.000141
Reviewing Previous Paper	46.4636	43.5	0.000095
Taking Notes	2.2909	2.0	0.000091
No Of Subjects	2.2500	2.0	0.000055
Class Discussions	56.7818	57.0	-0.000027
Peer Disturbance	44.6455	46.0	-0.000052
Class Skipped	3.3591	2.0	-0.000052
Procrastination	2.2909	2.0	-0.000089
Seeking Feedback	2.5000	2.0	-0.000137
Sleep Affecting Class	19.7864	10.0	-0.000159
Completing Assignments	34.1909	22.5	-0.000185
Lack Of Self Discipline	41.7273	38.5	-0.000186
Self-Directed Study	5.9045	6.0	-0.000194
Social Media	2.1182	2.0	-0.000348
Over Reliance On Memorization	3.2636	3.0	-0.000471

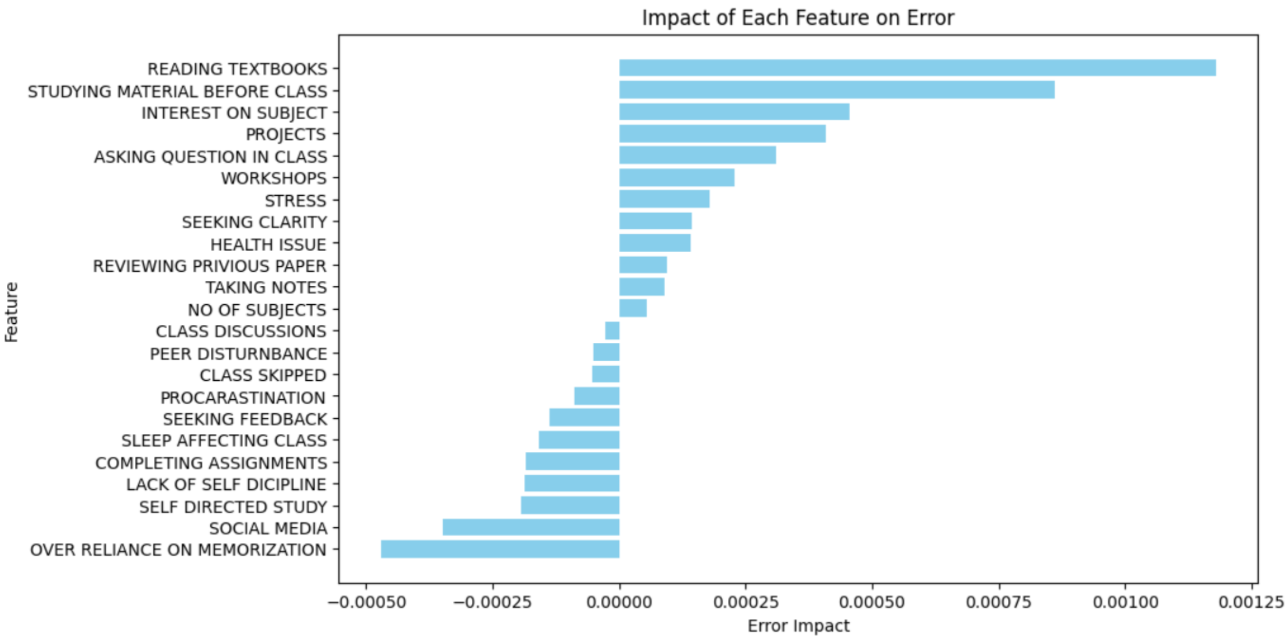

Fig 5.2 Impact of each feature on error for grade:2

TARGET 3			
LEARNING ACTIVITIES	**MEAN VALUE**	**MEDIAN VALUE**	**ERROR IMPACT**
Seeking Feedback	3.1682	3.0	0.003342
Peer Disturbance	40.4136	39.0	0.001262
Workshops	2.8500	3.0	0.000955
Stress	4.7818	4.0	0.000658
Lack Of Self-Discipline	38.9318	40.0	0.000509
Self-Directed Study	5.9955	6.0	0.000300
Interest On Subject	2.7227	2.0	0.000153
Procrastination	1.8091	2.0	0.000140
Sleep Affecting Class	15.1500	1.0	0.000126
Over Reliance On Memorization	3.1545	3.0	0.000123
Health Issue	23.1773	5.5	0.000111
Asking Question In Class	1.7682	2.0	0.000102
Social Media	1.4864	1.0	0.000096
Projects	1.9273	2.0	0.000082
Reviewing Previous Paper	46.5864	41.0	0.000010
No Of Subjects	1.4818	1.5	-0.000096
Seeking Clarity	1.6182	1.0	-0.000167
Studying Material Before Class	54.9182	50.0	-0.000172
Class Skipped	2.7636	2.0	-0.000282
Taking Notes	1.9682	2.0	-0.000353
Class Discussions	48.9727	44.0	-0.000618
Reading Textbooks	2.3591	2.0	-0.000674
Completing Assignments	37.7364	33.0	-0.000796

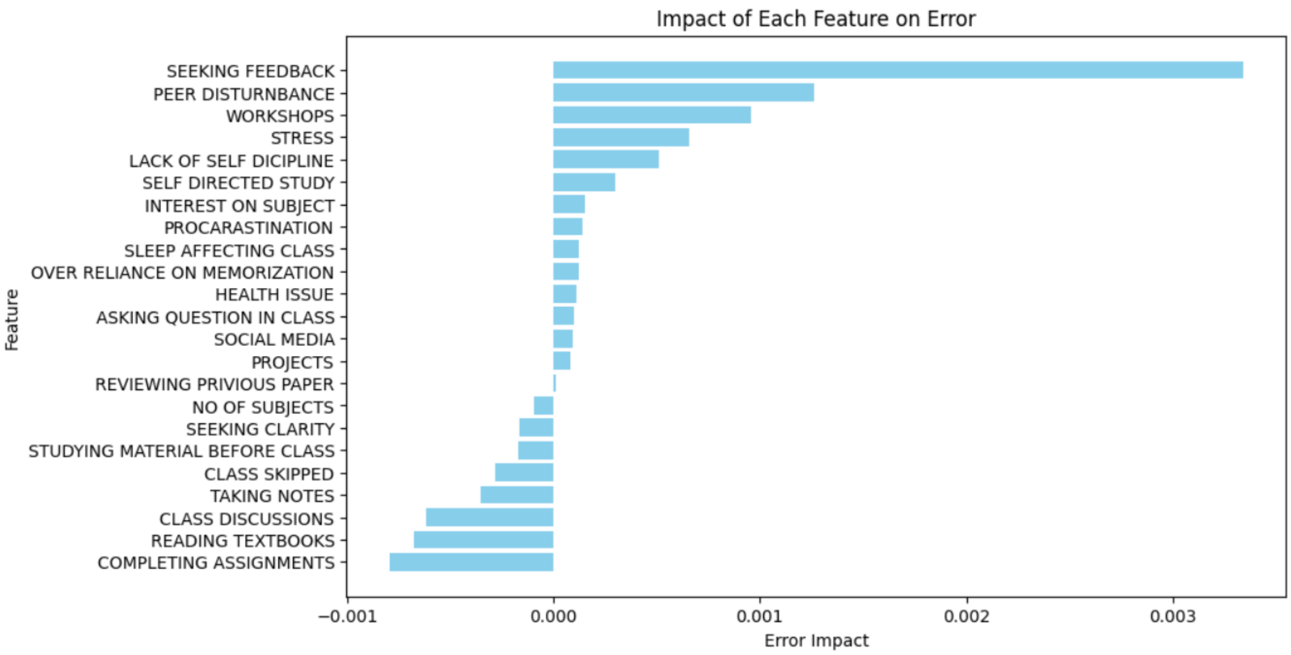

Fig 5.3 Impact of each feature on error for grade:3

TARGET 4			
LEARNING ACTIVITIES	MEAN VALUE	MEDIAN VALUE	ERROR IMPACT
Completing Assignments	36.8955	31.5	0.001576
Class Discussions	46.6364	50.0	0.001386
Reading Textbooks	2.0909	2.0	0.001193
No-Of Subjects	1.3227	1.0	0.000769
Taking Notes	2.0591	2.0	0.000681
Asking Question In Class	1.6864	1.5	0.000529
Studying Material Before Class	49.0636	48.0	0.000467
Interest On Subject	1.9682	2.0	0.000412
Sleep Affecting Class	15.0682	1.0	0.000409
Class Skipped	3.5000	3.0	0.000390
Seeking Clarity	1.2000	1.0	0.000283
Health Issue	15.8909	1.0	0.000131
Reviewing Previous Paper	45.4455	50.0	0.000035
Procrastination	1.8136	1.0	-0.000121
Over Reliance On Memorization	3.2091	3.5	-0.000195
Projects	1.6636	1.5	-0.000200
Social Media	1.1727	1.0	-0.000242
Self-Directed Study	5.4864	6.0	-0.000285
Lack Of Self-Discipline	47.4545	45.5	-0.000381
Stress	4.0318	3.0	-0.000564
Workshops	2.3273	2.0	-0.001089
Peer Disturbance	37.3273	37.0	-0.001373
Seeking Feedback	2.0273	1.0	-0.002298

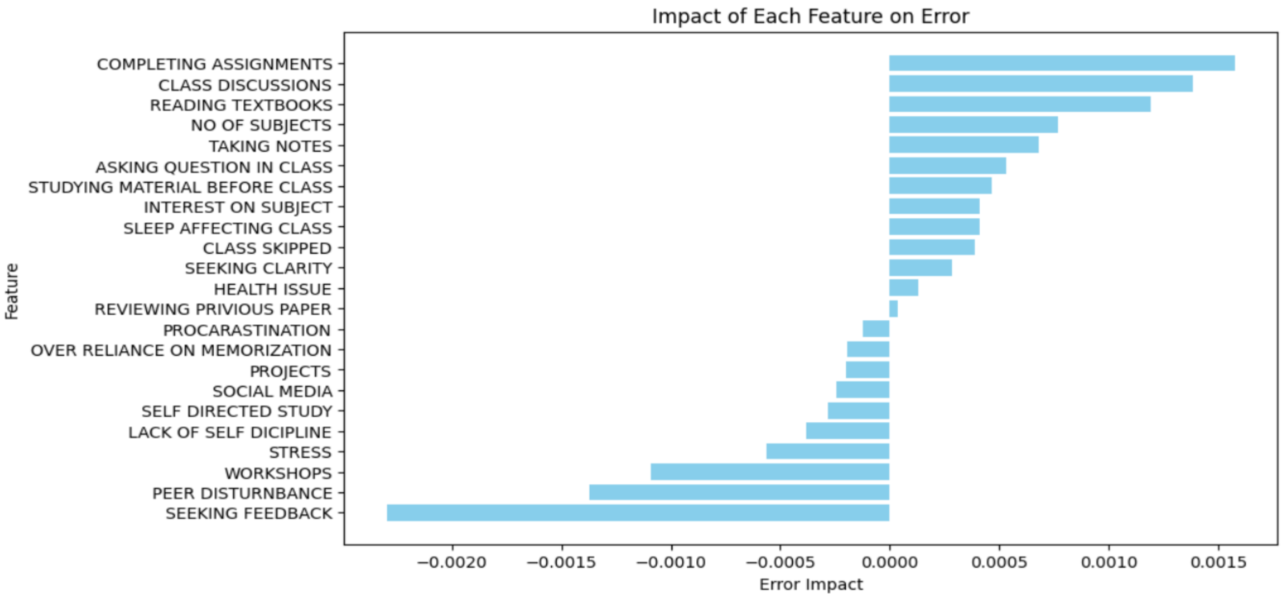

Fig 5.4 Impact of each feature on error for grade:4

5.2 RESULTS ANALYSIS:

For Students Scoring 80 to 100:

- Features such as time spent on reading textbooks, studying material before class, rate of interest on the subject, and time spent on collaborating on group projects have higher mean values, indicating a positive impact on academic performance.
- Factors like stress, health issues, and lack of self-discipline have lower mean values, suggesting a negative impact on academic performance.

For Students Scoring 70 to 80:

- Similar trends are observed for positive impact factors such as time spent on reading textbooks, studying material before class, and collaborating on group projects, but with slightly lower mean values compared to the 80 to 100 range.
- Negative impact factors like stress and health issues still show lower mean values, indicating their continued negative influence on academic performance.

For Students Scoring 60 to 70:

- There's a noticeable decrease in the mean values of positive impact factors such as studying material before class and collaborating on group projects compared to higher scoring ranges.
- Negative impact factors like stress, lack of self-discipline, and procrastination show higher mean values, suggesting a stronger negative impact on academic performance.

For Students Scoring 50 to 60:

- The mean values of positive impact factors decrease further, indicating a weaker association with academic performance.
- Negative impact factors such as stress, lack of self-discipline, and asking questions in class have higher mean values, indicating a more pronounced negative impact on academic performance.

Overall, as the student scores decrease, there's a trend of diminishing positive impacts and increasing negative impacts on academic performance across various factors. This suggests that addressing negative factors and reinforcing positive habits becomes even more crucial for students with lower scores to improve their academic performance.

CHAPTER 6
CONCLUSION AND FUTURE PLANS

6.1 CONCLUSION

The research paper aimed to ascertain the key factors that significantly impact students' academic performance, with the primary objective of assisting educators in enhancing learning environments. Through the collection and analysis of primary data under controlled conditions, the study aimed to determine the relative importance and effects of various factors on student grades.

In addition to academic factors, the study also examined critical aspects such as student stress levels, usage of social media and sleep quality. These findings contribute to a broader understanding of the diverse influences on student success, extending beyond traditional academic metrics.

Ultimately, the research provides valuable insights for educators, empowering them to customize their strategies and interventions to better support student learning and overall well-being.

6.2 FUTURE PLAN

In order to further improve this study the increase in the number of students participating in the data collection process should be done. In addition to adding to the amount of data, that would introduce new variables into the discussion of which ones are most crucial.Then, further processing techniques can also be tried for comparison.

Subsequently, the methodology employed in this study can also be transformed into an application that teachers can use to monitor the outcomes attained semester by semester across several classrooms, providing them with a clearer picture of the adjustments they need to make.

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CHAPTER 7
BASE PAPER
Appendix A Base Paper

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An artificial neural network for exploring the relationship between learning activities and students' performance

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Sunway University, Malaysia

A R T I C L E I N F O

Keywords:
Artificial neural network
Student's performance
Learning analytics
Questionnaire design
Data flow optimization
Multilayer perceptron model

A B S T R A C T

This paper identifies the most significant learning factors impacting undergraduate academic performance using artificial neural networks (ANNs) and controlled student data collection. As higher education becomes increasingly common and important, finding the best ways to help students optimize their studies is vital. Questionnaires gathered data on student behaviours and achievement from five classes within a semester, constraining variability to compare learning activities directly. The questionnaire captured engagement, psychological factors, effort, course load, time management, and performance data. Statistical and exploratory analysis investigated the dataset. A multilayer perceptron model was developed, using backpropagation and cross-validation to optimize predictive accuracy. The model identified class attendance, sleep quality, and questioning during lectures as most correlated with high grades. Additional patterns emerged around research participation, motivation, cramming, and theoretical studying. This research demonstrates new techniques for associating detailed study behaviours with academic achievement through strictly controlled student data collection and the application of artificial neural networks for predictive modelling. The constrained variability in the dataset allows for isolating the impact from specific learning activities. The controlled student data and machine learning-driven predictive modelling provide information on the optimal grouping of student effort across engagement, health, and studying factors.

1. Introduction

Higher education is more common than before. As most higher education teaching approaches rely on the self-discipline of the students, a lecturer normally has less monitoring on the students. Therefore it is important for the students and lecturers to identify the learning activities that are able to contribute to the understanding of the students in the subject [1]. This in turn can lead to better educational outcomes and contribute to the success of students in their future careers.

In today's fast-paced world, students and lecturers are growing increasingly disconnected. Lecturers have different expectations for their students and are left disappointed when students fail to conform to them [2]. Likewise, students also find themselves in a disarray with their expectations of the type of education they are to receive at university [3]. Furthermore, students find themselves in an increasing amount of stress for getting better grades and that trend does not seem to be going anywhere anytime soon [4] In fact, if anything, it is growing. Students now face more stress not only due to external stressors like social media [5], but also academic pressure in performing better in a highly competitive environment that is created around the students [4]. On the other hand, we are now in an era where new information is constantly being added to their subject matter. With so much information available, it is easy to lose focus. It is therefore important to know not only where time is more efficiently spent studying for a subject but also to identify the factors that have a causation effect on a student's performance.

In an ideal situation, teachers track their students progress to enhance the efficiency of the learning process continuously throughout a semester with the knowledge of where and what to fix and what factors to watch out for. This further extends to the teachers being able to have a way of knowing if the topic alongside with their teaching methods is effective and results in higher productivity for the students. However, most of the time the only point of reference that the teachers can evaluate if their teaching methods are sufficient is the results of their students in the various coursework and exams that they take along with any separate feedback they receive from their students [6]. Teachers are also unable to know how engaged the students are with their teaching and the subject at hand. At the same time, artificial intelligence (AI) use is increasing in the world with increased applications of domains under it such as data mining, prediction etc. Similarly, progress is also seen in the world of education with Chen et al. [7] doing a review on this field and finding 4519 publications from 2000 to 2019. They found the use of AI in a wide field of subdomains notably performance prediction. Similarly [8] who also did

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a review found the term “predict” being a part of one of the main topics in the use of AI with similar results also being mentioned by Holmes et al. [9]. These show not only the growth of AI in the field and its increasing focus in the world of education [10], but also the viability of using it for prediction of factors and aspects. Garett and Young [11] explored the use of AI in social audio and the potential future it has and in more recent times [12] used ANN in COVID-19 modelling to predict future patients and deaths. As seen in these reviews however, one of the areas where AI use is lacking is in the area of predicting factors and learning related activities that affect student performance. Most papers dealing with prediction do so at predicting student performance or behaviour [7–9,13,14] where it leaves a small gap in expanding the use of AI in education through the use of other sub-domains. To address this issue, this study proposes an artificial neural network (ANN) with primarily collected data to measure the impact of different factors allowing the teachers and educators to know what factors correlate positively or negatively with the student’s grades in their class. This can allow them to design more effective teaching strategies and interventions to support struggling students. Further, this study proposes to do so whilst having the data be collected in a much more controlled environment as well allowing for more accurate representative results.

The main aim of this paper is to identify the most significant factors that affect student performance. To do so, it focuses on the design of the questionnaire for the collection of data on student’s learning activities and the processing of the collected data to evaluate the factors that affect student’s performance. The remainder of the article is divided into six sections. First the considerations during the designing phase of the questionnaire will be discussed. Then the content of the questions being asked will be discussed. The next section will then discuss the factors affecting student’s academic performance before the design of the questionnaire for data collection. The collected data will then be analysed using statistical approaches and exploratory approaches. An ANN will then be constructed to provide a predictive model for student’s performance in terms of grades using the learning activities as inputs. The hyperparameters of the trained ANN will be analysed to investigate the significance of the inputs, i.e. the learning activities on the output, i.e. the student’s performance.

This paper demonstrates new techniques for associating detailed study behaviours with academic achievement through the combination of strictly controlled student data collection and application of artificial neural networks for predictive modelling. The constrained variability in the dataset allows for isolation of the impact from specific learning activities, providing new insights into optimal grouping of student effort across engagement, health, and studying factors.

2. Review of relevant work

The use of AI in education is widespread, one of the most common areas and use cases is in prediction using different models. Dogan et al. [15] did a systematic review examining 276 publications on AI in online distance education. They found use cases in AI in various fields including for teaching/learning, prediction of student behaviours and enabling of personalized learning. An important conclusion they reached was on the importance of using human-centered AI rather than purely technically driven solutions. Rastrollo-Guerrero et al. [16] in a review found 64 papers using various AI and machine learning models in attempting to predict student performance, student dropout, student activities and recommended activities and resources. In their review, they found ANN, Decision Trees (DT) and Support Vector Machines (SVM), models as the most commonly used in these papers.

Looking at each of the models, DT were used in [17] to predict student performance by measuring their cognitive and non-cognitive features. They were also studied in [18] in a review on decision tree algorithms prediction performance.

Moving on, Hussain et al. [19] did a comparative study using Naive Bayesian (NB), ANN, SVM, DT and regression in predicting student difficulties in learning and found ANN and SVM as the most accurate. Likewise Hernández-Blanco et al. [20] found in a systematic review that ANN in deep learning based models achieved higher accuracies than machine learning counterparts in 67% of the papers they reviewed. Musso et al. [21] predicted key educational outcomes such as degree completion and grade point average using a backpropagated ANN. They used various background information from the students to map and reach those outcomes.

Zhao et al. [22] did a study using logistical regression and SVM in predicting student performance to see if they would get certification and managed to achieve an 84% accuracy with SVM. Villagrá-Arnedo et al. [23] did a similar study using SVM to predict student performance and categorize them into 3 categories of performance. Hashemi Petrudi et al. [24] did a study using for performance measurement in higher education institutions using Fuzzy Delphi method and Best Worst Method in identifying a list of performance indicators.

3. Questionnaire design consideration

3.1. Performance factors

When discussing the factors that could affect performance, there are both factors inside the classroom as well as those outside. Table 1 shows the different factors affecting student performance and the studies associated with them. Looking at factors inside the classroom, the significance of student attendance is always a major discussion in every institution. Some have the options of attending or watching pre-recorded online lectures but for those that do not have that option, lack of attendance means missing out the subject material being taught. Caviglia-Harris [25] shows that students who attend class more often end up with better academic performances in comparison to those who do not. Similarly, Ancheta et al. [26] found similar results with student attendance affecting student performance. Academic workload is the next important factor with Kizito et al. [27] and Yang [28] both finding that increased academic workload can lead to decreases in academic performance as well as increases in burnout. Academic workload here is represented through both the number of classes a student has in a semester as well as the amount of work/assignments they have.

Interest in the subject being studied is also an important factor. Interest in a matter often leads to putting more effort and performing better in related tasks overall. Afzal and Ali [29] mentions that students who were engaged enough with a subject to investigate it before the formal teaching were found to more likely score higher marks for that subject. Another similarly related factor is the effort from the student to study the materials before attending the class. This is the case where students study the lecture material or perform the practical tasks before the actual class in order to be more prepared. Chen and Lin [30] found that students who do this on average end up doing better in class and having higher performance scores. Onah and Anamezie [31] also found similar results in secondary school students learning physics where academic interest led to increased performance and achievement.

Part of the interest in classes as well as the effort put into learning can also be described by the student’s self motivation. Steinmayr et al. [32] and Kusurkar et al. [33] both found self motivation to be a very important and impactful factor towards student performance with increased motivation having a positive effect on not only performance but on almost all aspects of a student’s learning including factors such as student well-being as well as overall engagement and happiness with their studies [34].

There are some aspects that a student does not necessarily have full control of. Stress is one such factor. Saqib and Rehman [35] and Pascoe et al. [36] show that stress has been shown to negatively affect one’s life in all aspects and this includes academic performance. Sleep is another important factor that helps regulate the body and the mind. Phillips et al. [37] mentions how lack of quality sleep has led to detrimental effects in memory, focus, and cognitive function all of which are related to studying regardless of in the classroom or self-learning.

Table 1
Factors affecting student performance.

Factors	Student attendance	Interest in class	Stress	Sleep	Self-motivation	Academic workload
Caviglia-Harris [25]	X					
Afzal and Ali [29]		X				
Phillips et al. [37]				X		
Kizito et al. [27]						X
Onah and Anamezie [31]		X				
Saqib and Rehman [35]			X			
Steinmayr et al. [32]					X	
Kusurkar et al. [33]					X	
Ancheta et al. [26]	X					
Yang [28]						X
Pascoe et al. [36]			X		X	
Chen and Lin [30]		X				

3.2. Data gathering

Megel and Heermann [38] discussed multiple ways to perform data gathering such as through interviews, focus groups, document reviews, questionnaire surveys and so on. Megel and Heermann [38] also discussed how questionnaires, since allowing for anonymity, are a good option to use if anonymity is needed. If sensitive data is collected, as it often requires non-anonymous data collection, it will result in detrimental effects to response rates as more will be unwilling to participate. Therefore being able to do the survey anonymously is an encouraged requirement. Furthermore, Navarro-Rivera and Kosmin [39] discuss how a questionnaire allows minimal involvement time by the participants. In a world where attention is measured in milliseconds, a survey shines its light in comparison to other data gathering methods such as interviews or ethnographies for time and attention required. The next reason that a questionnaire is favourable comes from the question of "what data is required?". Megel and Heermann [38] also further discusses how, while interviews allow for high-quality qualitative data, when only quantitative data that no further explanation or in-depth answers are required, questionnaires are better suited. A further advantage is that questionnaires allow for the flexibility of the researchers to choose and base their questionnaire around existing ones. This gives an advantage of having a reference to an established work [40]. This allows easier documentation, as there will not be unplanned spontaneous modification to the flow in the data collection process.

Because questionnaires maintain anonymity, participants have the option to participate in the study without the researchers' knowledge. Therefore in the next subsections we will discuss the non-response bias and response bias before going into some practices that are discouraged in designing a questionnaire.

3.3. Non-response bias

When sampling is performed, not all members of the target group respond, and thus not a full circle of answers can be received but rather only answers from that group are received. This will give rise to non-response bias [41]. Choi and Pak [42] mentioned a big issue with questionnaires is the effect of participation bias in the outcome to make the results inaccurate. This is vital in this study as participation bias potentially happens for students who did not score as highly in the subject. This would sway the results heavily in favour of the top students and thus make the study invalid as it fails to consider all the students of different varieties.

Thus, anonymity is practised to counter this issue. Megel and Heermann [38] discusses how an advantage of questionnaires is that as the respondents do not have to show themselves or reveal any personal details, it gives them the extra comfort from behind an anonymous screen which will allow for more responses. Choi and Pak [42] then talks about how non-monetary incentives such as a personalized message sent through email may help getting more respondents to perform the survey. The questionnaire will also be non-disguised, meaning the participants will be briefed of the use of their data and the outcomes that is to achieve. This gives the survey an extra human touch as the participants will not feel like lab rats undergoing tests. This potentially leads to higher response rates. Toepoel and Schonlau [43] and Kennedy and Ouimet [44] further discussed how giving a questionnaire's introduction and explanation section a more human touch will raise empathy in the participants and thus increase the number of participants.

As the presence for non-response bias can be assumed, the data and program will have to be adjusted accordingly to deal with the issue. If it is found that the participants who answered were all of those who got >60% for example, then the data analysis will be adjusted to see where these students spent their time that allowed them to get these higher scores. Harris and Namboodiri [45] recommends a basic inverse relationship that can be established with the results in that an assumption could be made that students who do not share the same factors like the higher scoring students can be expected to not score as well. This can still help with pattern identification as it would give a base as to what to look out for in a student's performance in a semester.

3.4. Response bias

Biases may still arise when the participants respond to a survey. This is coined as response bias. Due to the nature of the study, most questions asked should be as close-ended as possible, leaving little room for interpretation or subconscious misrepresentation of the questions asked to avoid response bias. Quantitative answers provide another solution for reducing the response bias. Therefore if the nature of the study allows, most of the questions should have quantitative response. Still, the questions must be worded such that they do not cause any sort of response bias. Ornstein [46] recommended that the wording must be concise, valid, and succinct, with phrasing to be done in as much of a neutral demeanour as possible. This also helps in keeping the questions as straight to the point as possible, leaving any unnecessary wordings behind.

3.5. Logistics consideration

Incentives and human touch alone cannot make a good questionnaire that can maximize the response rates and the accuracy of the responses. For the purpose of maximizing the response rate, Arora [47] suggested that the questionnaire should be made simple and straightforward, Ornstein [46] mentioned how the questions should not require assistance in answering them and the questions should flow logically. If the questions are too complex, the response rates will take a hit as the participants may abandon the questionnaire when they have issues understanding the questions [48]. Burchell and Marsh [49] brings up questionnaire length as another important factor in keeping the response rates high. Long questionnaires lead to interest lost in participants. When taking into consideration the target group being university students, time and attention are not plentiful resources. The questionnaire will, therefore, be kept short where possible. A total completion time of fewer than two minutes would help keeping the interest up while completing the questionnaire.

Most of the algorithms used to predict student performance are either limited by the algorithm itself or by certain contexts of data gathering and analysis. Most of the related literature did not perform primary data gathering, instead they received their information based on other sources such as the school registry. This causes limitations as only certain factors can be extracted this way. Most of these literature only use Grade Point Average (GPA) results with the students background information as factors for consideration [50–52]. Factors that were not considered are ones that involve the engagement and psychological conditions of the students such as the stress levels in the semester or how engaged they were with a subject, which can only be found through directly asking them. This work will perform primary data gathering as this provides the flexibility to collect any relevant data that are considered important for the study. As for the literature that did their own data gathering, it is mostly done at a mass level where large groups of students are generalized as a whole and processed collectively. This approach ignores the effect of the factors such as different subjects, different students of different ages, and different teaching methods. To counter this, a non-probability sampling method was undertaken in the form of the study asking students who were in the same class so that the differentiating factors to be analysed would be from the students themselves, allowing the rest of the variables would be controlled. By controlling the data, it firstly allows for much greater real world accuracy with the data that is collected being more consistent and reliable. As a consequence of that, the results obtained are then more representative too and more importantly, can paint a picture for that specific group of students. Next, the environment be controlled more for data collection also allows for less noise to be present in the data which helps the ANN in training. This is helpful as it allows for a more data-driven environment to be present which in turn helps the ANN in its training. This also enables the comparisons between different classes in order to analyse the factors importance change between classes.

3.6. Questionnaire design

The questionnaire is divided into multiple sections of which the participants are uninformed. The purpose of the sectioning is solely for the researcher to compare and analyse the data. The questionnaire itself, is asked onto students participating in a specific class in a specific semester meaning all education and university related factors are controlled as the participants would be in the same environment. This is true for all 5 modules asked and allows for the study to be unique in its approach where the results obtained would be much more real world accurate and for it to provide better discussion.

The 10 questions chosen to be asked in this study were not backed by an industry expert but rather were supported by the various research works looked at by this study. The most significantly related and impactful factors were then scoured and formed the theoretical model of which the questions stem from, the theoretical sections are discussed below. The other factor on how the 10 questions were defined comes from the anecdotal hypothesis of which variables would be the most applicable when discussing students of this particular university. The importance of this is that by asking more applicable questions, it allows the results obtained in the end to then be more significant and real world accuracy.

This questionnaire is divided into six sections composing the theoretical base which comprise of pre-standing interest, psychological condition, personal effort, semester structure, time management, and lastly the actual grade of the student. The first three sections, pre-standing interest, psychological condition, and personal effort, are factors intrinsic to the students. The following two sections, semester structure and time management, focus on the logistics of the students life. The last section provides the ground truth to which the effect of different factors are analysed. All of these combined help make up the conceptual model of the various factors affecting student performance.

Section A – Students pre-standing interest in the subject

This section focuses on the student's interest in the subject. It aims to capture the relationship of the interest a student has in a topic with their performance and effort in the subject. The questions are answered on a linear scale with values ranging from 0 to 100 with 0 representing "never'' and 100 representing "very often".

Question 1: How often did you do research on the subject before it was taught?

This question aims to identify both how much a student knows about a course before it is introduced as well as the amount of interest and effort they are willing to put into it. This is based on the belief that the students who engage enough to investigate a subject before it is being taught are more likely to score higher marks for that subject [29].

Question 2: How often did you ask a question about anything that was taught in the subject?

This question aims to see how engaged a student is with the subject. Asking questions to clarify anything that is taught in the classroom is a good sign that a student pays attention in the classroom and has at least some form of engagement with the lecturer. This question works on the basis that the students who actively try to ask questions on the subject matter and therefore are engaging in self-improvement are more likely to score in the subject. One thing this question failed to account for, however, is the students who do not need to ask anything as they have no issue understanding any part of the content.

Question 3: How often did you study the material to be taught before class?

This question aims to see how dedicated a student is on a subject. It seeks to see if they would take the route of performing the work/studies required before they are even taught of it. This is based on the idea that students who do this on average end up doing better in class and having higher performance scores [30].

The next question was answered with a range from 0 to 100 whereby 0 denotes "not interested" and 100 denotes "very interested".

Question 4: How would you rate your interest in the subject?

This question directly asks the section's headline of their interest to the student. This question seeks to get a direct view of how much the students gauge their interest in the subject. It will be used to investigate the correlation with previous questions.

Section B – Student's external factors in life

This section asked questions regarding a participant's life outside the classroom. It aims to find the link between the factors outside of the classroom and performance inside the classroom. The presumption is that certain negative factors that are unrelated to the classroom can still affect a student's performance. The questions are also answered in a linear scale with values ranging from 0 to 100 with 0 representing "never'' and 100 representing "very often".

Question 5: How often would stress from outside affect you in the classroom?

This question aims to see the effects of stress on a student's performance. Stress is a known factor that negatively affects life in all aspects [35]. Likewise, the higher the stress level of a student, the more likely they are to perform badly in a class [35]. This question does not ask students about their stress level directly as everyone perceive their stress levels differently, therefore potentially causing the data to be skewed. Instead, it asked the participants how much their stress affects them in the classroom. A drawback of this question however is its open-ended nature which can cause potential issues with students understanding it.

Question 6: How often would your quality of sleep affect you in the classroom?

This question investigates the relationship between sleep and a student's academic performance. Sleep was already known to be a very important biological mechanism to keep a human healthy in all aspects of life and lack of sleep has shown to be detrimental to memory, focus, and cognitive function [37]. This question is not asking for students to rate their sleep but rather to rate its effects they experienced on their studies. This helps giving the students an image of the question and gives better data on the effects of sleep as opposed to just asking about their sleep quality.

Section C – Student's efforts at improving

This section investigates the student's efforts at self-improvement. It aims to find the link between the amount of time and hardwork put into the subject in relation to their performance at the end. The presumption was that the more effort a student puts in, the better their performance would be. The question in this section is also answered in a linear scale with values ranging from 0 to 100 with 0 representing "never" and 100 representing "very often".

Question 7: How often would you not attend Lectures/Tutorials?

This question looks into the relationship between a student's performance and their absence in their classroom. It assumes the negative effects on the student's results that would accompany a student missing out on their classes.

Section D – Student's university factors

This section investigates the factors relating to their classroom or university. It looks into the aspects of a student's educational life that are not directly controlled by them. This section aims to see how important the role of the university is in a student's performance. The question is answered with multiple-choice options.

Question 8: How many subjects did you have during the semester?

It is assumed that the more subjects a student has, the more workload they have and therefore they are less likely to score for each one.

Section E – Studying partition factors

This section investigated the amount of time a student spends studying different materials. The materials are categorized into 3 sections, theoretical material, practical material, and through 3rd party materials. It aims to see which aspects time is better spent studying in.

Question 9: Based on the amount of time you spent studying by reading the theoretical material (Slides, book, etc.), doing practical work (Tutorials, re-doing practical work, etc.) and through the Internet for information (YouTube, Websites, etc.) please state accordingly the relative amount of time you spent studying below.

This question asks the student to separate the different studying methods they have into different ratios. It is assumed that a student has three ways of studying for a subject. First, through theoretical means such as reading the slides provided or by reading the subject textbook. Second, through practical means such as performing the tutorial/lab work. Third, through the internet where they could watch videos and go on articles for information.

Section F – Student's grades factor

This section takes in the final grade the student achieves for the subject. It is also used as the value for the output layer of the ANN.

Question 10: What was your final result for the subject?

This question asks for a student's final result which is then used as the ground truth for the output in the ANN. This is the most important question as this variable will be used to judge the importance of all the other questions above it.

3.7. Data gathering

An online survey was chosen as the way to gather data. It provides both anonymity and allows for faster and easier data collection. Rather than creating the survey by scratch, QuestionPro was chosen as the service to create the surveys from using the templates and provided there as the base for the survey. Multiple forms of question types were chosen but primarily for most of the questions, a linear scale option is given. The students who are asked to take part in the survey are all sent an email at the same time with their student id being used as their recipient information to maintain anonymity. To help not overload potential students who would overlap in multiple classes that are being asked to participate, a 3-week boundary is put in place between sending out emails. The 3-week boundary also serves as a block to any potential mix-ups in answers from students who are being asked to participate twice for two different classes. Depending on the classes involved, the sample size varied from as low as 41 to as high as 234 with an aim of getting as many responses as the research could. This ends up with an average response rate of about 25%–35%. With regards to the actual participants themselves, the target group of the study is university students (18–28 years old) of a specific class in their first year of study and beyond. Some students may have been asked to participate more than once due to being in different classes but each time they were asked to give answers concerning that specific class they took that semester. Students are assumed, in general, to be familiar with surveys and have familiarity with answering and processing the questions. This, therefore, means they are assumed to be able to conceptualize linear scales and therefore are entrusted to give high quality answers on their own. The students are also asked to participate on regards to the class they took not later than one semester after taking that class to minimize any invariances in the data they provided as compared to what had actually happened due to memory fades.

4. Data analysis

This section discusses the different approaches that are relevant to analyse the questionnaire data. These approaches are categorized into two types, statistical analysis and exploratory analysis.

4.1. Statistical analysis

Before any visual representation is done, the data would first be processed into different descriptive statistics [53]. Under descriptive statistics, the ones that will be used by this study are the mean, standard deviation, median, interquartile range, skew, and range along with the mode for the question "Number of subjects taken in the semester". These statistics are being used because the data collected through the questionnaire is best suited for these types of analysis measures. Albers [54] states that the goal of these statistics must be established, and a clear objective defined in using them instead of simply finding random data values to make sure that there is reasoning for the specific use of descriptive statistics. These descriptive statistics would allow for the finding of outliers as well as any trends that may be visible [53,54]. They will not however be used for any sort of basis on conclusion makings, the data prediction section will be dealing with those instead.

There are multiple types of statistical analysis tools available, but for this research, only certain measures deemed useful and fitting for the research are considered. The statistical analysis measures used are discussed in the following section.

Mean is the average of all the data for a certain question. It is calculated by adding all the data points and then dividing by the total number of data points. The mean is taken as a measure as it helps to provide a single value to conceptualize the data overall. It is used to get an idea of what the average values are from the data and what inferences therefore can be made from it.

Mean is applied to all the questions to show where most students stood and felt on certain factors and therefore give a pretext on what predictions and assumptions could be made from the data before any prediction was done.

It is important to note, however, that the mean is influenced by outliers and skewed data. Likewise, some data was found to have outliers, therefore, skewing the mean by a small amount to its direction causing the mean to not be as a strong analytical tool for those questions.

Standard deviation is the value that helps identify how spread out the values are from the mean. In this case, it helped show how varied the dataset was.

Median is the middle value that separates the two halves of data. With the existence of outliers in the data, the median helped give a separate but accurate measure of the average value. Since its purpose is mostly like the mean, it was used as a parallel tool in identifying average values and helped give a picture of where the data stands.

Interquartile range indicates the spread and variability of the data by calculating the difference between the upper and lower quartiles. It helps to understand the middle 50% of the values sorted in ascending order. Therefore it identifies the range where most of the values are located in the dataset as well as spotting any outliers too.

Range is the difference between the highest and lowest data points. While not as an accurate measure for spread as other methods such as Interquartile range, the range still gave a value for the measure of dispersion that was found in the data.

Mode is the data value which was chosen the most often. In the study, it was only applicable to one question, the number of subjects a student had, and was an easy way to see how many subjects the majority of students had.

4.2. Exploratory analysis

Exploratory analysis will be done through representing the data retrieved from the survey in a visual manner. Rae et al. [53] mentions the different methods such as bar graphs, line graphs, pie charts, bubble graphs, box and whisker plots, etc. Through the graphs, the relationships between variables can be established and more specifically the relationship between any of the factors and their final grade outcome. Furthermore, Albers [54] shows that the data can be binned into specific categories such as different grade groups (Those who got <60, <70, etc.) that allows for specific patterns to be identified within each of the bins. Albers [54] however mentions that if there is a low number of participants, the binning outcomes may not be as meaningful due to the low variability of respondents and thus should not be used as a basis for any conclusion and instead act as a possibility.

After all calculation-specific analysis, it is important to display the data through graphical means to get a better visual representation. Most of the data are collected in the form of linear scales with the user giving a value between 0 and 100, therefore most traditional graphical methods such as pie charts or line graphs are not applicable since the data values between different users are not directly comparable. Bar graphs and bubble graphs are more appropriate in this case.

A bubble graph is used to display three dimension data. In this specific case, the bubble graph is used to display the three dimensions of question number, rating group and size of the group. The Y-axis being the question number, the X-axis the rating group and the bubble representing the size of that group, to display the average values given for each question. The bubble graph gives an overall visual comparison of where the data stood in relation to the questions and the values that the students gave for them.

Table 2
Models used for classification.

Paper	SVM	RF	Naive Bayesian	ANN	Regression based
Cortes and Vapnik [55]	X				
Yoo et al. [56]		X		X	
Zou et al. [57]					X
Farjah et al. [58]					X
Abu Amra and Maghari [59]			X		
Silva et al. [60]				X	
Hamedi and Dirin [61]			X		
Kang and Ryu [62]		X			

A bar graph is a graph that compares different groups of data using bars against the same metric. This study uses bar graphs to compare the values a participant gives for each question and the average values all the participants give for each question. It helps to give a visual guide on the pattern of the answers provided. A bar graph was also used at the end once data prediction using ANN had been completed to visualize the impact of each input factor on the output.

5. Performance estimation

5.1. Introduction

Before a model is chosen, it is first important to see what are the differences between ANN and some other models as well as what benefits they may hold over other models. One key difference between ANNs and other models is the way they process data. ANNs are inspired by the structure and function of the human brain, and they process data in a way that is similar to the way neurons in the brain process information. Other models, such as decision trees or linear regression, process data in a different way. At the same time, they are able to capture complex, non-linear relationships in the data, making them well-suited for tasks where the relationships between variables may be complex or difficult to model using traditional statistical methods.

In this study, the data collected will be a part of a supervised data set and as a result, classification would be performed in finding out the most impactful learning factors towards student performance. Table 2 shows a list of models used by other papers when performing classification related tasks.

From the results obtained, it can be seen that a wide variety of models/tools can be used when performing classification. Between the papers reviewed, each model had a specific use case that enabled it to be used for that particular research. From the various papers as well as separate reviews done on classification based algorithms [63,64] and ANN based algorithms [65,66], Table 3 is drawn showcasing their differences as well as their advantages and disadvantages.

From Table 3, it can be seen that generally, each model can work well in different scenarios based off of their advantages and disadvantages. For this situation however, ANNs can work well firstly, due to their advantage in working with imbalanced data which this study has to a small extent due to receiving more responses from better scoring students. While they are not immune from the negative effects from it, they can still work around it, this is in contrast to other algorithms such as SVM that do not work as well with imbalanced data. Other than that ANNs can work well with non-linearly separable data where other algorithms such as Naive Bayes, due to their more simple approach, do not work as well with non-linearly separable data. This is significant due to the many hidden relationships that are present in the data collected as well as the need for the study to want to explore those potential relationships that may otherwise not be present if done with a simpler algorithm such as regression.

ANNs are used to estimate the performance of the students based on their pa- rameters obtained from the questionnaire. The effectiveness of the estimation will be able to provide insights into the key features.

Table 3
Models comparison.

Algorithm	Advantages	Disadvantage
Artificial neural networks (ANNs)	Flexible with the ability to work with a wide range of use cases in different context due to its ability to work with and adapt to a wide range of data	Can be prone to overfitting
		Is more of a black box when it comes to understanding it
	Can recognize patterns and relationships between data	Sensitive to hyperparameter tuning meaning different results can be obtained depending on how the tuning is conducted
Naive Bayesian	Simple to interpret results Flexible with different kinds of data	Does not perform as well on more complex relationships
		By nature assumes features are independent of each other which can cause inaccuracy
		Prone to potential biases
Support vector machines (SVMs)	Good with higher dimensional data	Does not work as well with imbalanced datasets
Logistic Regression	Works well with continuous data	Not as suitable for predicting labels
	Can provide measure of uncertainty on the results obtained	Handles linear relationships better than non-linear ones
	Simple to interpret results	More affected by outliers
Random forests	Very low chance of overfitting	More complicated to understand the relationship between the various trees in achieving the results
	Easier to interpret results	Less accurate when there are less features to work with

ANNs work on the basis of connections through artificial neurons and nodes and therefore closely resemble their biological counterpart that are found in brains in all sorts of living things [67]. They are complex model and prediction tools that can be used in describing situations that have real world similarities [68–70]. They are defined by three layers, the input, hidden, and output layer, each with different functions. The input layer takes all the information given to it sending it through its neuron to the hidden layer where the data is then summed and sent to the output layer to determine the results [71]. In each neuron, an activation function will be used to determine the activation status and if activated an output will be produced.

5.2. Data pre-processing

Nawi et al. [72] found that pre-processing greatly helps in enhancing the accuracy and computational efficiency of an ANN training process. Nawi et al. [72] and Kuźniar and Zajac [73] then discuss the multiple options available for pre-processing such as principal component analysis (PCA), scaling, Z-Score, DecimalPoint and Min-Max Normalization, and Standardization. Tudu et al. [74] used PCA and normalization to pre-process data for a back-propagated multilayer perceptron ANN to classify black tea. The results showed that while the raw data provided an accuracy of 60.25%, the normalized data increased the accuracy to 93%. Mustaffa and Yusof [75] used the three different normalization methods, Z-Score, Decimal-Point and Min-Max Normalization, in both input and output data to find out the accuracy in predicting dengue cases. The paper found that decimalpoint normalization achieved better accuracy than the other two methods, but all methods produced better accuracy compared with using the raw data for processing. Raudys and Skurikhina [76] discussed the impact weight initiation has for ANN training. The work showed that with smaller training samples, adding random weights can be beneficial for the accuracy of the ANN. Raudys and Skurikhina [76] also looked into the potential factors that have effect on the accuracy of the ANN and discussed the potential of random weight initialization over multiple cycles to have a positive effect on ANN performance and accuracy.

As the literature review showed, data pre-processing is a vital step to improve accuracy. There is however no single best pre-processing method as it is dependent on the type of data and training. To achieve the best accuracy, the pre-processing methods were all taken and applied with the other factors staying the same, and the ones that caused the highest accuracies were chosen. The first method used was Min-Max normalization to normalize and scale all the values to a similar range for better comparison. This was done due to the high range of values possible values (0–100) that the different questions could have as their answers.

To make up for the small number of data values from data collection, the data was appended three times to increase the total amount of data threefold. While this will not help to increase the diversity and variety in the data, it helps with training instead. Separately, data generation is also done using Synthetic Minority Oversampling Technique (SMOTE) where new data points are generated between the minority class data points to fill in a more evenly made data set. Imbalanced-learns SMOTE API was used to perform this.

5.3. Network architecture

There are multiple network architectures available for ANN. Table 4 is shown to give a representation of some of the findings. It is found that the multi-layered backpropagated neural network is the commonly used architecture. De Albuquerque et al. [50], González and DesJardins [77], Wang [78] and Al-Shawwa et al. [79] used a multilayer perceptron along with back propagation for predicting student performance, application behaviour, risk of drug use in high school students and temperature and humidity respectively. As mentioned earlier, an ANN has three types of layers, input, hidden, and output layers. A multilayer perceptron is an ANN where the neurons in the hidden and output layers use a non-linear activation function. The multilayer perceptrons that are used are feedforward networks that get trained via back-propagation which is when the difference between the predicted and actual values gets sent back to the network as data to be processed. This, therefore, makes the multilayer perceptron with back-propagation a supervised learning technique. Dharmasaroja and Kingkaew [51] used Decision Tree and Regression (DTREG) for predicting learning performances in the medical field. DTREG breaks down the data into subsets while developing a decision tree for prediction using the predictor variables (value of target variable). Binh and Duy [52] used a 3-layer multilayer perceptron to predict student's performance based on learning style. Moghaddam et al. [80] and Aghababaeyan and TamannaSiddiqui [81] both used ANN with multilayer perceptrons to predict stock market index and the Tehran stock market respectively.

Table 4
ANN comparison among studies.

Author	Prediction tool	Application	Accuracy	R^2
De Albuquerque et al. [50]	ANN-MLP	Predicting student performance	98%	–
González and DesJardins [77]	ANN-MLP	Predicting application behaviour	80.2%	–
Wang [78]	ANN-MLP	Predicting the risk of drug use in high school students	–	–
Al-Shawwa et al. [79]	ANN-MLP	Predicting temperature and humidity	100%	–
Dharmasaroja and Kingkaew [51]	ANN-DTREG	Prediction of learning performances	98.1%	–
Binh and Duy [52]	ANN-MLP	Predicting student's performance based on learning style	80.63%	–
Moghaddam et al. [80]	ANN-MLP	Predicting stock market index	–	0.9622
Aghababaeyan and TamannaSiddiqui [81]	ANN-MLP	Forecasting Tehran stock market	97%	–

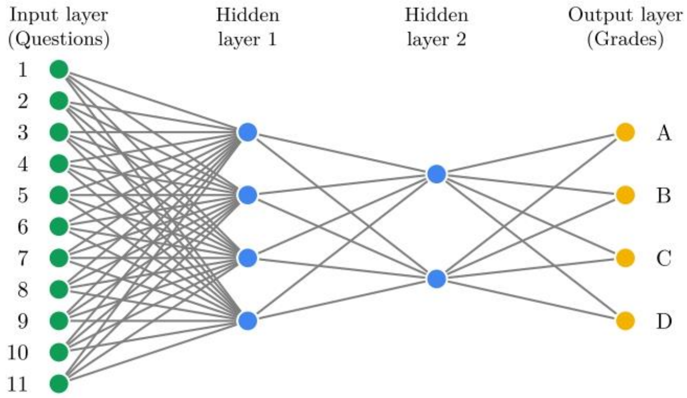

Fig. 1. ANN design.

Golnaraghi et al. [82] also found that a back-propagated neural network performed better at modelling construction labour productivity than other methods including Radial Base Function Neural Network (RBFNN), General Regression Neural Network (GRNN), and Adaptive Neuro-Fuzzy Inference System (ANFIS).

With regards to the activation function, there are many types available. Nwankpa et al. [83] discusses the benefits and drawbacks of the various activation functions. However, for this study, only a certain group of the most popular activation functions are investigated, including sigmoid, ReLU (Rectifier), tanh and linear activation functions.

The architecture of the ANN used in this study is heavily influenced by previous research works such as [50,52,77–79]. To find the most optimal structure, a cross-validation confusion matrix is constructed where multiple ANNs are trained and the one with the highest reported accuracy is chosen.

The ANN is a multilayer perceptron. It is a feedforward neural network where the connections would only go in one direction and would not form a cycle. Recurrent networks are ones that have internal feedbacks and thus form cycles. This allows them to have a form of memory which makes them useful for any predictions that require previous information. Since that is not required here, feedforward networks are more applicable in this situation. The ANN has 4 layers in total, 1 input layer, 2 hidden layers, and 1 output layer with the hidden layers having 4 and 2 neurons each. This is shown visually in Fig. 1.

The number of neurons is an aspect that has to be managed well as if there are too many neurons then overfitting would happen but if there are too little neurons then the ANN would fail to adequately solve the problem. First, there are rules available to determine the number of neurons as introductory guidance and the one that was followed was for the number of hidden neurons being less than twice the size of the input layer. In this studies case, with 11 input neurons, that means that there should be a total of less than 22 hidden neurons. As seen, however, with the limited amount of data that is available, having that many hidden neurons would cause overfitting to happen and therefore a different method is needed. The next rule that is followed is by keeping the number of neurons below a certain threshold determined by the number of input and output neurons where the number of hidden neurons should be 2/3 the size of the input layers added to the size of the output layer [76]. This threshold is then calculated to being 11 hidden neurons. Ultimately however, to determine the ideal number of neurons, trial and error is needed and is performed starting with many neurons at first within the constraints of the two rules above and then over time, reduced to a number that has the best of both worlds.

The input layer has 11 neurons, with each neuron representing the values of a question answered by the student. The input variables are:

1 Research done by student on the subject
2 How often a student would ask a question in class
3 How often would a student study the class material beforehand
4 The students Interest in the subject
5 The impact of external stress on a student in the classroom
6 The impact of sleep quality on a student in the classroom
7 How often a student would skip classes
8 The number of subjects a student had in that semester
9 Comparatively, the amount of time spent studying through theoretical material
10 Comparatively, the amount of time spent studying through practical class material
11 Comparatively, the amount of time spent studying through external methods such as the internet

The output layer on the other hand has 4 neurons based on the last question in the questionnaire asked to the students. The variable of the questions being:

1. The student's final grade percentage for that subject

The ANN has a classification-based model which uses the grade percentages and classifies them into four categories. For the activation function, each neuron has an activation that is used to determine the

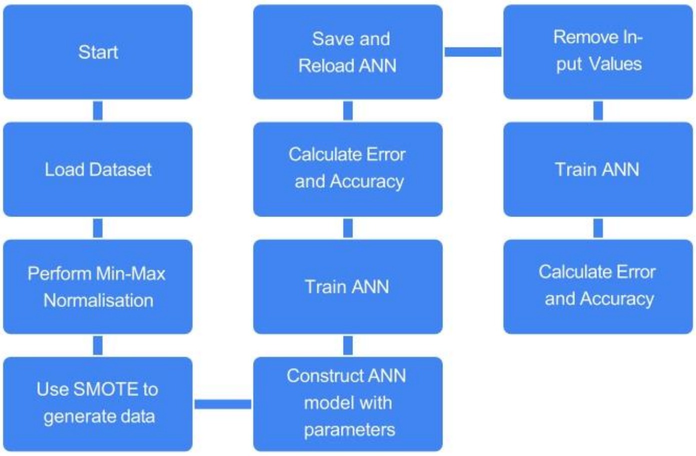

Fig. 2. ANN training process.

Table 5
Output neuron information.

Neuron (#)	Output variable	Grade percentage
1	A	70% and above
2	B	60% to 69%
3	C	50% to 59%
4	D	49% and below

output of that neuron given a certain input [84]. For this study, four activation functions were investigated sigmoid, ReLU, tanh, and linear activation. ReLU was eventually chosen as it brought upon the highest accuracy values with regards to the data available and this also fell in line with its popularity in being used in a lot of ANN [80,81].

Table 5 shows the 4 different classifications made with the grade percentages being in row with the British grading system.

5.4. Training

In combination with the fact that the ANN is supervised, back-propagation training is used to train the ANN. Back-propagation works by taking the difference between the actual output of each neuron and the expected output as error. The weights of each layer would then be updated accordingly using the error. A step by step process of this would be:

- Initialize the weights W_i with either a random small value or fixed value
- For every training sample X_i loop
  - Input the instance X_i to the neural network and calculate the output O_j
  - For every output and hidden unit calculate the delta values
  - Using the delta values and learning rate calculate the new weights for each neuron
- Loop until the termination condition is met

To start, a train-test split of 80% was used with regards to the Pareto principle [85]. More variations of the train-test split however were also performed and tested to obtain the best accuracy and in the end, a split of 85% was found to give the best accuracy.

With regards to weights initialization, the weights were initialized with the same values at first but eventually random small initializations of the weight values were used as they brought on higher accuracy values.

A learning rate of 0.001 was first used following scikit-learns MLP-Classifier supervised neural network. Over time however and through different trial and error methods, a learning rate of 0.015 was found to provide the best accuracy.

A visualization of the whole training process is shown in Fig. 2.

6. Case studies

This section will now discuss the findings of the study in relation to the original objectives and problem statement. Each sub-section is separated by each of the classes that were asked to participate.

In relation to the error impact values being described in each section below, a higher error impact means that the ANN resulted in having less accuracy without that specific question in place as an input value and therefore is more significant to the overall output of the ANN. On the other hand, any negative values could mean many things and there is no exact clear-cut answer as the negative values would represent a more inhibitory connection as opposed to an excitatory connection which is found in those with a positive value. This, therefore, causes there to be no discussion on the factors which had a negative impact value in terms of their impact on the student's grade and rather their answer values are looked at instead in terms of their magnitude to see what the students responded for them and where they stand in relation to other classes.

Students of five modules were requested to complete the questionnaire before the aforementioned analyses were applied on the collected data. The target group were university students (18–28 years old) of a specific class in their second year of study and beyond. A student may have been asked multiple times due to being in different classes but each time they were only asked to give answers in relation to that specific class they took that semester. Students were also be assumed to be familiar with surveys and have familiarity with answering and processing questions. This therefore meant they are good at conceptualizing linear scales and therefore can be entrusted to give higher quality answers of their own. The students were also asked about the class they took not later than 1 semester after to minimize any invariances in the data they provide in relation to what had actually happened due to fading memory. The major limitation here is that it reduced the potential sample population and the actual adopted sample size greatly. The selected modules are modules taken by the students from various programmes of the same class in the same semester. Module I and II

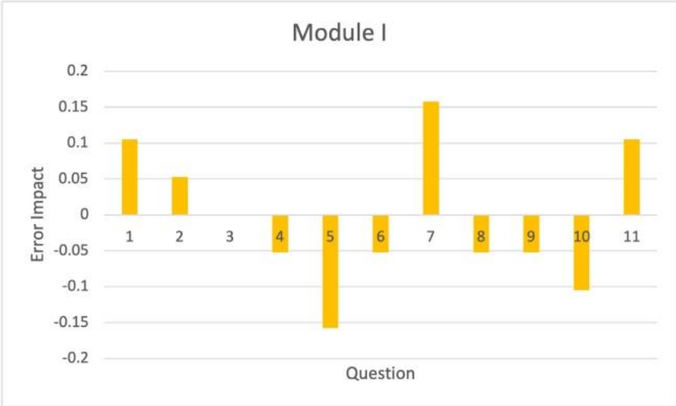

Fig. 3. Error impact (Module I).

Table 6
Accuracy of values of the ANN.

Class	Total accuracy	Precision	Recall	F1 score	Participants (#)
Module 1	94.7%	97%	87.5%	92	32
Module 2	92%	96.3%	92.3%	94.3	37
Module 3	89.8%	90.3%	94%	92.1	33
Module 4	93.3%	97.5%	79%	87.3	24
Module 5	90.5%	95.6%	87.5%	91.4	34

Table 7
Analysis for Module I.

Question (#)	Error impact	Mean	Standard deviation	Median	IQR	Mode
1	0.105263	24.18	27.5	15	28	–
2	0.052632	39.4	29.4	42.5	37	–
3	0	25.4	27.9	20	31.8	–
4	−0.052647	68.6	22.7	70	21	–
5	−0.154821	48.1	30.3	49	43	–
6	−0.052631	62.7	30.5	66	51.5	–
7	0.1578954	14.6	16.7	8	24.8	–
8	−0.067121	–	–	–	–	5
9	−0.105263	41.5	21.3	45	20	–
10	−0.107164	38.1	14.9	35	13.8	–
11	0.108412	20.4	18.2	16.5	23	–
12	–	70.6	9.4	70	13	–

are basic linguistic modules, module III to V are computing-related modules. Module III and IV are algorithmic modules and module V focuses on the system design.

6.1. Overall accuracy

Table 6 shows the accuracy values of the ANN. Confusion matrices were used to check for their accuracy and all modules were able to achieve near 90+% accuracy and above in classification. This combined with the high precision and recall values show that the ANN not only gives highly viable results but that it is strong in predicting the right factors as well.

6.2. Module I

Firstly, looking at what the average grades of the students who participated were using Table 7, question 12 shows that on average, the students scored 70 with a lower range of values. This shows that the students who accepted to participate in this study were on average better scoring students and therefore, have caused the results to be biassed towards them as they are not fully representative of the whole classroom. Figs. 3 and 4 help give a better projection of the answer values received.

In terms of factors having a bigger impact on this class, students who had conducted research before taking the course ended up having a better result than those who did not. Question 1 demonstrates this by having an error impact of 0.105263 and an average answer of 20, indicating that even minimal research had a positive impact on the students' grades. Separately, skipping classes had a significant impact on students' grades. This is demonstrated by question 7, which had an error impact value of 0.1578954 and an average answer of 11. Even students who skipped a relatively small number of classes experienced a negative impact on their grades. Next, students choosing to study the least using the internet tended to have better results. Question 11 shows this with an error impact of 0.108412, and in having an average answer of 22, it suggests that the students in this class did not rely heavily on internet resources to study. Finally, students who asked questions in the class were more likely to have a smaller increase in their results. This is seen in question 2 with an error impact of 0.52632, and its average answer of 41 showing that students in this class asked questions more often than not and that therefore helped with their grade. For the rest of the factors, the negative error impact limits the amount of discussion that can be done on them with regards to the effect they have on the grade but they can still be discussed to see where their values stand. Student's for this class had high levels of interest in the subject as shown in question 4 with an average answer of 69. Likewise, the students reported that their quality of sleep was affecting them to a noticeable extent through question 6 with an average answer of 64. Furthermore, stress too was affecting students to a higher degree as seen in question 5 with an average answer of 49. The students spent most of their time studying using the theoretical material and to a slightly lower extent, the practical material as well with questions 9 and 10 showing this through their average answers of 43 and 37, respectively. Finally, most of the students participating in this survey had 5 subjects in their semester as seen in question 8 with a mode of 5.

6.3. Module II

For Module II, through Table 8, the average grade obtained by the students who participated is 68. This gives the same issue as Module I where the students who chose to participate were mostly better scoring students. However, there is higher variance and range present here in the values and therefore is a slightly more varied dataset. Figs. 5 and 6 provide visualization for the values obtained in Table 8

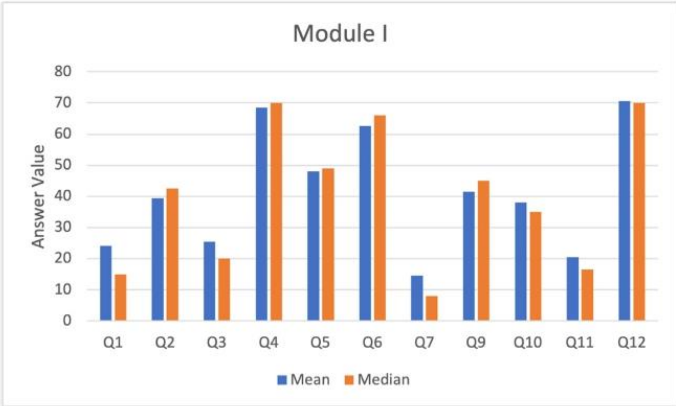

Fig. 4. Answer values (Module I).

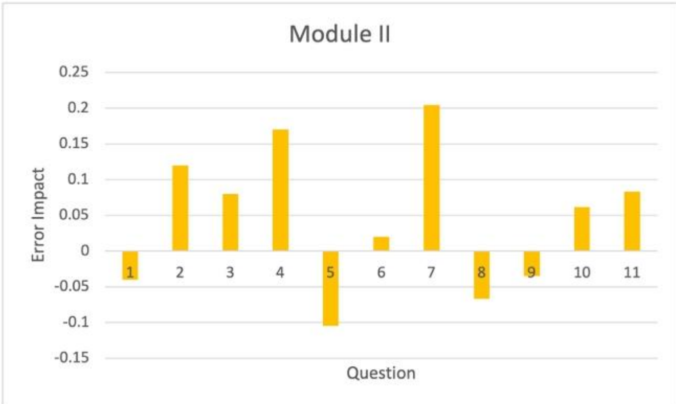

Fig. 5. Error impact (Module II).

Table 8
Analysis for Module II.

Question (#)	Error impact	Mean	Standard deviation	Median	IQR	Mode
1	−0.04873	26.7	26.2	20	49.5	–
2	0.12427	35.1	26.3	30	47	–
3	0.08124	22.9	27.9	10.5	33.75	–
4	0.1732	56.8	27.8	60	31.75	–
5	−0.104612	51.9	33.2	60	51.5	–
6	0.02402	64.2	33.4	76.5	53	–
7	0.20467	22.2	25.9	10.5	24	–
8	−0.0671	–	–	–	–	5
9	−0.03512	38.7	19.1	42.5	25	–
10	0.06173	30.4	16.2	30	20	–
11	0.0845	30.9	25.6	20	27.5	–
12	–	67.9	16.1	70	18.8	–

Looking at the most significant factors, students who asked questions during class ended up having a better result than those who did not. Question 2 shows this by having an error impact of 0.12427, and by having an average answer of 32, it shows that the students were asking questions sparingly but even so was enough in having a better result in the end. Beyond that, students who had larger amounts of interest in the class tended to have a better grade. This is shown through question 4 having the error impact value of 0.1732, and by having an average answer of 58, it shows that the students had higher interest in this class which resulted in a better grade. Next, like in Module I, students choosing to not attend classes resulted in having a worse grade. Questions 7 shows this with an error impact of 0.20467, and in having an average answer of 16, it shows that most of the students only skipped a few classes yet were still affected by this in their result. Furthermore, students who studied the material before class were more likely to perform better. This is seen in question 3 with an error impact of 0.08124, and its average answer of 17 shows that most of the students in this class did not study the material beforehand as often. Beyond that, students who had a worse quality of sleep tended to get lower grades. This is seen in question 6 with an error impact of 0.02402, and with an average answer of 70, it shows that most students were affected by large amounts of poor-quality sleep and this in turn is affected their grades negatively. Finally, students who spent the same amount of time studying using practical material and the internet caused a noticeable impact on their result. This is seen through questions 10 and 11 with their error impact values of 0.06173 and 0.0845, respectively. Just as before, the rest of the factors had negative impact values, therefore, limiting their impact on the discussion. Students for this class performed lower amounts of research on the subject beforehand as shown in question 1 with an average answer of 23. Likewise, the students reported that overall stress was affecting them to a decent extent as seen in question 5 with an average

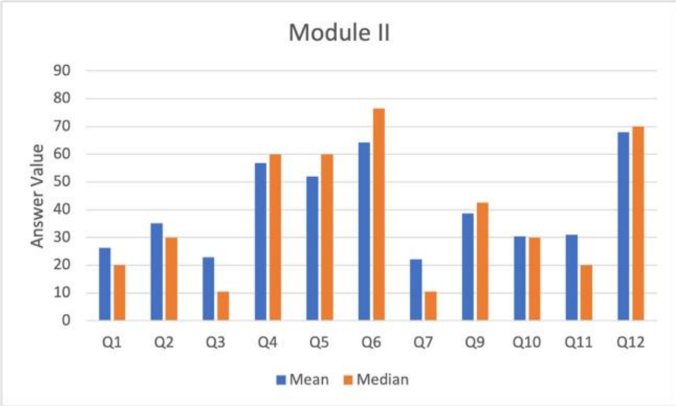

Fig. 6. Answer values (Module II).

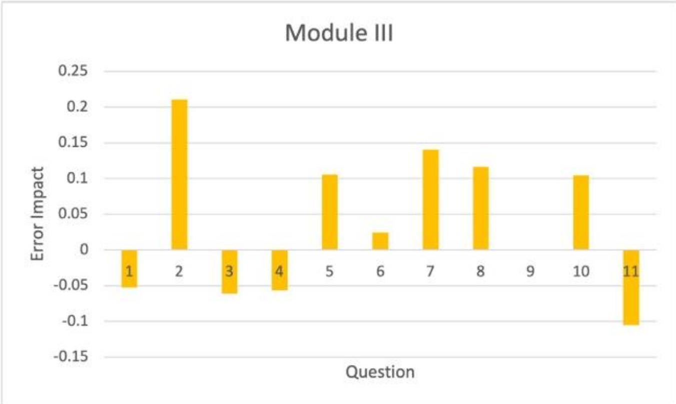

Fig. 7. Error impact (Module III).

answer of 56. Separately, most of the students in this class had 5 subjects in their semester as shown in question 8 with its mode value of 5. Finally, as seen in Module I again, the students spent most of their time studying using the theoretical material where it is shown through question 9 with an average answer of 40.

6.4. Module III

Module III had an average grade of 49.4. This is the first class that has had a lower than average grade and therefore shows a different perspective in terms of answers in comparison to the other classes where mostly the higher scoring students answered. It still suffers from being skewed to the lower end but gives for a good comparison of data. Figs. 7 and 8 provide visualization for the results obtained above in Table 9.

With regard to the most significant factors, students who asked questions during class performed better academically. This is seen through question 2 with an error impact of 0.2101, and with an average answer of 33.1 similarly to Module II, it shows that most of the students asked questions often that helped with the results. Next, like in Modules I and II, students who skipped classes tended to perform worse. This is shown through question 7 having an error impact value of 0.14034, and by having an average answer of 41.4, it shows that the students in this class skipped class quite frequently and subsequently ended up with a worse grade. Additionally, stress and quality of sleep were significant factors that impacted academic performance. Questions 5 and 6 shows this with an error impact of 0.10523 and 0.02464 respectively, and in having average answers of 53.1 and 57.6, it can be seen that while stress is a bigger factor, quality of sleep is important too where most students again like in the other classes report low levels of quality sleep. Furthermore, students who took more classes during the semester tended to have a greater impact on their academic performance. This is

Table 9
Analysis for Module III.

Question (#)	Error impact	Mean	Standard deviation	Median	IQR	Mode
1	−0.0526	22.7	22.1	17.5	22.5	–
2	0.2101	33.1	27.2	23.5	38.25	–
3	−0.0614	19	24.0	10.5	20.75	–
4	−0.05712	33.1	27.1	28	43.75	–
5	0.10523	53.1	22.2	58.5	37.25	–
6	0.02464	57.6	18.6	56.5	24.25	–
7	0.14034	41.4	28.9	38	42.5	–
8	0.1161	–	–	–	–	5
9	0	66.4	20.4	75	29	–
10	0.1046	21.4	10.3	15	16.5	–
11	−0.010263	12.4	12.5	10	10	–
12	–	49.4	16.3	46.5	23.5	–

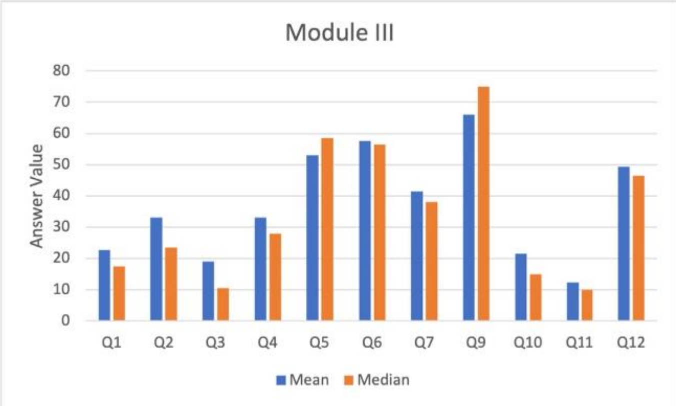

Fig. 8. Answer values (Module III).

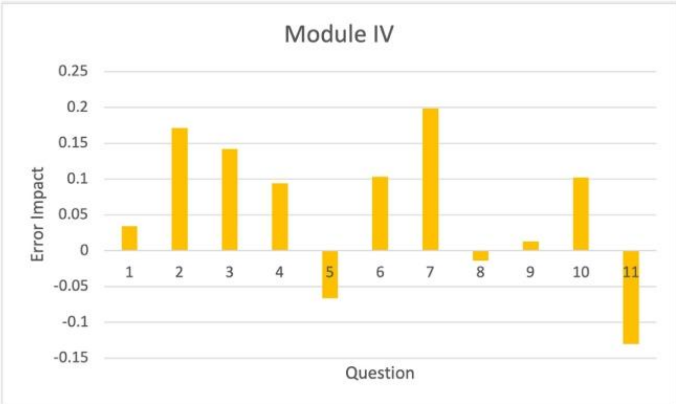

Fig. 9. Error impact (Module IV).

shown through question 8 with an error impact of 0.1161 and a mode of 5. Beyond that, studying using the practical materials was found to be more impactful on the grade. This is shown through question 10 with an error impact of 0.1046, and its average answer of 21.4 shows that it was the second most popular studying method. Like before, the following factors all had negative error impact values. Lower amounts of research were done by the students as shown in question 1 with an average value of 22.7. Similarly, the students did not study the material prior to the class as much as seen through question 3 with an average value of 19. Likewise, most of the students had lower levels of interest for the class shown through question 4 with an average value of 33.1. Finally, studying using the internet was the least popular studying method in this class and also the only one with negative impact having an average value of 12.4 which is less than a quarter of the amount of time spent studying using theoretical materials with an average value of 66.4 as seen in question 9

6.5. Module IV

Module IV had an average grade of 59 with almost all the responses being in the range of 51 to 65 making it the second class alongside Module III that has a lower average result. Table 10 and Figs. 9 and 10 help give a better visualization of the results obtained as well.

Table 10
Analysis for Module IV.

Question (#)	Error impact	Mean	Standard deviation	Median	IQR	Mode
1	0.034123	13.2	15.9	5.5	21.5	–
2	0.171243	20.6	11.7	16.5	18.3	–
3	0.142165	7.67	12.0	0.5	10.3	–
4	0.094312	32.21	18.1	29	19.8	–
5	−0.06675	58.8	21.1	65.5	27	–
6	0.103436	67.2	13.4	71	14.3	–
7	0.198723	54.3	21.6	60.5	29.3	–
8	−0.01423	–	–	–	–	5
9	0.013451	60.2	12.9	65	20	–
10	0.102345	26.3	8.40	25	15	–
11	−0.130412	13.5	7.73	10	5	–
12	–	58.7	7.94	54.5	10.5	–

Examining the most impactful factors as also seen in the previous classes, students who attempted and asked questions during class ended up with a better grade. This is seen through question 2 which has an error impact of 0.171243, and by having an average answer of 18, it shows that students who ask even a few questions tend to perform better. Furthermore, students who studied the class material in advance rely on in getting better results. This is shown through question 3 having an error impact value of 0.142165, and by having a really low

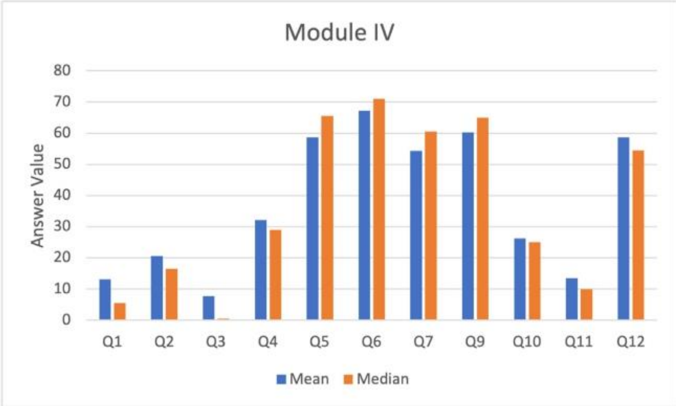

Fig. 10. Answer values (Module IV).

average answer of 3, it shows that the students who put in the minimal effort but still effort nonetheless by studying the material were more likely to score better. Separately, like in Module III, students having poorer quality of sleep tended to be much more affected by it in their studies. Questions 6 shows this with an error impact of 0.103436, and in having an average answer of 69, it follows suit in showing high reported answers for bad quality of sleep affecting students and for this class, having a visible significant impact on their grades. Students who skipped their classes gravitated towards underperforming as well. This is shown through question 7 with an error impact of 0.198723, and its average answer of 57 which is the highest reported for this question shows that not only did most of the students skip half the classes but they ended up scoring worse because of it too. Students in this class spent most of their time studying using the theoretical material shown in question 9 with an average value of 63. This at the same time had a smaller impact on their grade with an error impact of 0.013451. Likewise, they spent half the amount of time studying using the practical material as seen in question 10 with an average value of 25 but this had more impact overall on their grade with an error impact of 0.102345. On a smaller extent, students who did research beforehand on the subject were more likely to slightly perform better. Question 1 shows this with an error impact of 0.034123, and with its average answer of 9, shows that most of the students did very little research before taking the subject. Moreover, students who were more interested in the class tended to get better grades. This is seen through question 4 with an error impact of 0.094312, and its average answer of 30 shows that most of the students had at least some form of interest in the class. In terms of the negative impact factors, students in this class in line with the other classes had higher levels of stress affecting them in the classroom with question 5 showing this with an average answer of 62. Beyond that, most of the students also similarly had 5 subjects that semester as seen in question 8 with its mode of 5. Finally, studying using the internet for this subject was the least popular method seen through question 11 with an average value of 11 denoting the lowest value out of all the classes.

6.6. Module V

Module V had an average grade of 66 with most of the responses being in the range of 57 to 75. It like Modules 1 and IV has a smaller range of values and therefore most probably suffers from being skewed towards the better-graded students. Figs. 11 and 12 provide better visualization for the results in Table 11.

Focusing on the more important factors, students who had done research prior to taking the course ended up having a better grade.

Table 11
Analysis for Module V.

Question (#)	Error impact	Mean	Standard deviation	Median	IQR	Mode
1	0.1429	26.6	26.6	19.5	45.3	–
2	0.0952	48.9	29.8	49.5	46.8	–
3	−0.048	21.9	23.6	19.5	19	–
4	−0.095	62.3	23.9	67.5	30.8	–
5	0.1401	43.9	30.7	43.5	48	–
6	0.0952	70.3	28.3	77.5	48.75	–
7	0.0871	27.6	26.6	20	49.5	–
8	0	–	–	–	–	5
9	−0.053	45.2	20.2	41.5	27.8	–
10	−0.143	24.5	12.3	26	13.5	–
11	0.0476	30.3	15.9	31.5	24.8	–
12	–	66.0	9.3	67.5	11.8	–

This is seen through question 1 with an error impact of 0.1429 and by having an average answer of 23, it shows that most of the students performed some form of light research on the subject before taking it and that tended to help them score better. Next, students who skipped classes tended to have a bigger impact on their grade. This is shown through question 7 having the error impact value of 0.1578954 and by having an average answer of 11 just like the previous factor, skipping even a few classes can have bigger amounts of impact on the grade. Next, students who asked questions in class more often than not were more likely to score better. Question 2 shows this with an error impact of 0.0952, and in having an average answer of 49, it shows that most of the students were vocal about their questions in some way or another and this ended up being a positive trend for them in regards to their results. Furthermore, students in this class had their results affected noticeably due to stress and quality of sleep. This is seen in questions 5 and 6 with error impacts of 0.1401 and 0.0952 respectively and their average answers of 43 and 74 show that most of the students were not only affected by some form of stress but they also had very bad sleep quality which both of these factors tended to cause lower grades. Additionally, studying using the internet had the only noticeable impact on the student's grade with question 11 showing an error impact of 0.0476. Its average answer of 30 also shows it as the second most popular studying method behind studying using the theoretical material.

Looking at the negative impact factors, most of the students did not study the material prior to the coursework as frequently with question 3 having an average answer of 20. On the other hand, most of the students had high levels of interest for the subject with question 4 showing an average answer 64. Finally, studying using the theoretical

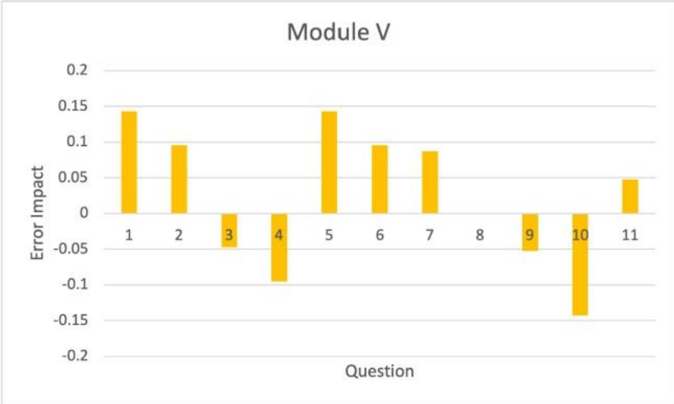

Fig. 11. Error impact (Module V).

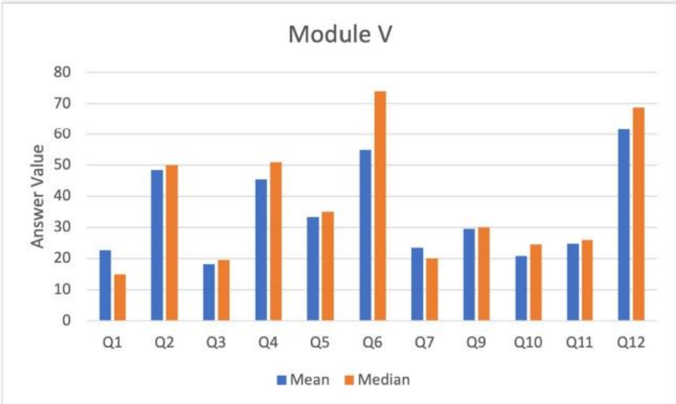

Fig. 12. Answer values (Module V).

material was the most popular method as seen in question 9 with an average answer of 43 while studying using the practical material was the least popular with an average answer of 24.

6.7. Collective analysis

Table 12 is constructed by summarizing the error values from the factors to see how often they had either a significant positive or negative impact. Their average value across all the classes is also collected to see overall what values and trends are shown. Fig. 13 shows the graphical version of the values obtained above in terms of positive and negative impact.

From Table 12, all the questions except for question 9 had a significant impact on a student's grade in one or more classes. Before any presumptive discussion is made, it must be noted that these values are representative of the specific scenario that the students were in, and while they do show trends and give better insights, they are only applicable in the unique scenario provided with them. Also, another note is made on the overall student's grade who participated in this study. With an average value of 62.1 which is otherwise skewed lower by Module IV which had an average value of 54.5 and Module III which had an average value of 49.4, most of the students who participated were higher scoring students which means they were more likely to engage in discussion, participate in group work and overall put in more

Table 12
Overall results comparison.

Question (#)	# of times found to have a significant impact on the grade	# of times found to have a negative value impact on the grade	Average value
1	2	2	15.7
2	4	0	32.4
3	1	2	13
4	2	3	52.2
5	2	3	52.6
6	2	1	70.4
7	4	0	26.8
8	1	3	5
9	0	3	52.7
10	2	2	26.9
11	2	2	20.4
12	–	–	62.1

effort in obtaining a better result [86]. This means that with regards to the values obtained here and the discussions that come after it, it is mostly representative of the higher scoring students who chose to participate in this study and therefore the results can be taken more likely as a means to improve the higher scoring students rather than to improve all students overall, though it to an extent is still applicable to them too. With that said, however, the discussion will take an overall

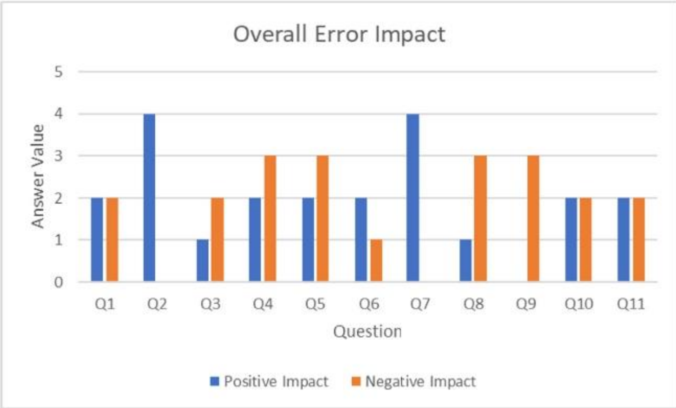

Fig. 13. Answer values (Overall).

perspective due to the notion that weaker students following suit in what stronger students do helps them improve too and feedback given to stronger students is most of the time applicable for weaker students as well [87]. Asking questions in the class and not attending classes both had the highest amount of impact across all the classes having had significant impact in 4 classes and 0 negative impact in any of the classes. Asking questions in the class as seen through question 2 had an average value of 32.4 covering all the classes showing that generally most of the students do not ask that many questions. There can be a multitude of reasons as to why this may be happening but shyness, language problems, relevance of the question and the personality of the teacher are all bigger possible reasons as to why students do not ask as many questions on average [88]. This, however, as seen from table 2.6 and the value before it, has a bigger impact on their grade which can be explained by showing that a student is not only paying attention in class but is also engaged with the subject and is more likely to want to aim for a better learning outcome and grade. Therefore, it should be looked into in improving a student's communication with their teachers in the hopes that they become more vocal with their doubts and questions that ultimately helps them improve in the long run. Likewise to that, not attending classes as shown through question 7 had a big impact too with an average value of 26.8. This value is skewed slightly higher due to Module IV having a value of 60.5 for this question while the rest of the classes had values in the range of 10 to 20. It however still shows that selfreported, most of the students did not skip as many classes which for this scenario can be explained with the fact that most of the students who participated were better scoring students and were, therefore, more likely to not skip class [86]. However, even the smaller number of classes skipped had an impact towards their grade showing again how this is another important factor that should be considered when trying to improve the student's results. Quality of sleep is next in terms of having greater impact having been impactful in two classes and negatively impactful in one. Its average value of 70.4 seen in question 6 shows that most of the students reported it as being a big factor that affects them in class. Though the results obtained show that it was not as impactful as its value suggests, sleep has always been known to be a negative factor for students impacting their focus and learning ability and with the high value reported here too, it is a factor that should be looked into to overall help students better manage their sleep and improve their sleep quality as compared to a lot of the other factors. This is a factor that while simple in idea of just having the students sleeping more, has had big negative consequences [89]. Researching before taking the subject is next in terms of impact being impactful in two classes and having had negative impact in two as well. It has an average value of 15.7 which indicates that most students did not conduct extensive research beforehand. The small amounts of research done by them however still accounted for a decent impact on their grade which could be due to performing research showing higher levels of interest and more willingness to learn, both of which are traits that would cause a person to more likely perform better. After that, interest in the subject and class comes next having had impact in two classes and negative impact in three. Its higher average value of 52.2 shown in question 4 shows that most students were more interested than not for their classes with the even value being skewed lower slightly due to Module IV having the value of 29. Interest in a subject was assumed to have a bigger influence on the student's grade as it was hypothesized that greater interest was expected to lead to more effort and better scores and while it still holds true it did not have the influence as it was thought to have [90]. This could be due to the difference between the interest a student had for the subject, and the way the subject was presented and taught to the student with the way assignments and exams were structured also contributing to the disparity between what a student expected and what they had gotten instead. Following that, stress affecting students in the classroom is next with impact in two classes and negative impact in three. As shown through question 5, its average value of 52.6 shows higher reported levels of stress which was seen across all classes. It was already known that students nowadays are having higher amounts of stress than before and so these results are consistent with previous research American Psychological Association [91] Likewise, as seen before in the literature review, stress did have an impact on the student's results but with the reported levels that the students mentioned the impact obtained was not as big as assumed to be. A potential reason could be that students can better cope with stress through methods such as listening to music or changing their perceptions of their stressors in life allowing them to mitigate its negative effects and therefore perform better [92,93]. This can be supported by the assumption that since most of the students who responded were higher scoring, they have better ways of coping with stress. Similarly, this also shows that it is not only lower-scoring students who deal with stress but that all students from all backgrounds have to deal with it. Studying the material before class had an impact in one class and had negative impact on two. It had an average value of 13 as seen in question 3 showing that studying the material before class was not as widely adopted by the students. This finding contradicts the assumption that studying before class has a high impact [94]. This could be explained by the act of studying before class not having as big of an impact on better scoring students who were the majority of whom responded. The lower value obtained as well shows that this can be compensated with the students spending efforts using other studying methods that allows them to still obtain a better grade. Similarly, the number of subjects a student had in the semester was impactful in one class and had negative impact in three. The vast majority of students reported having five subjects showing that even though the students had a lot of subjects to manage they were still mostly not impacted by it on a bigger degree. This however can be due to both not having enough data points of students who had fewer subjects, and the fact again that the students who participated in this survey are better equipped to manage such a workload. In terms of the three studying methods, studying using the practical material and internet had the highest amount of impact with both being impactful in two classes and having negative impact in two. Studying using practical methods was slightly more popular with a value of 26.9 compared to using the internet which had a value of 20.4 and which was the least popular method. The lack of using the internet can be explained by having enough material through the lectures and practical material such that using the internet is not needed as much except for gaining a different perspective. In contrast to those studying methods, studying using the theoretical material had the least amount of impact out of all the factors having had zero impact in any of the classes and having negative impact on three of them. Its average value of 52.7 on the other hand makes it the most popular studying method by a margin of 35.1 over studying using practical material. Its higher value is in line with what was assumed as the theoretical material is what is most likely to be asked from in the final exam leaving most of the information available to study for it available there. For some classes, the practical material is also used in the final exam causing those subjects to have more students spend time studying using them such as in Modules I and III.

7. Conclusion

This research paper aimed to find which factors are more significant towards a student's grade. It had the goal of helping educators by giving them a different set of information based on their students to allow them to better improve their learning environments for the students. It was also able to fill in the gap of research in analysing the effects of these factors by collecting primary data in a controlled environment and then processing the data to find the weights of these factors along with their significance with regards to the student's results. The paper was also able to shed light on some other important factors as well such as how most students responded with being stressed and having bad quality of sleep which are both important factors that have been recorded before. However, there were limitations in the research as not every variable could be perfected. Firstly, the number of participants received for each class was way below what was required for these results to be more accurate and while measures were taken to mitigate that as much as possible it still did have its effects on the results obtained. Next, the number of factors looked at as well were limited due to not wanting to overload the survey with questions that would potentially drive responders away, and so there are factors that might have been even more impactful than the ones discussed here that are not able to be known of. Both of these factors can be dealt with by having a more institutionalized mean of performing the survey such as making the survey a part of a bigger, more official movement by the university that covers more classes and can offer better incentives to the students for participating. This study can be improved by first, expanding the data collection both in terms of the number of students and classes asked and in terms of the factors asked as well. That would not only provide more data, but it would also bring different additional factors into the equation when discussing what factors are most important. Then, more processing methods can be attempted as well. Instead of just using a supervised ANN that uses backpropagation, unsupervised ANN and Recurrent NN are examples of other NN styles that can be used to compare accuracies and results. Next, the methodology used in this study can also be converted into an application that can be used by educators to track the results obtained semester by semester through different classes to give them a better visualization of what changes they need to bring.

CRediT authorship contribution statement

Kourosh Borhani: Data curation, Data analysis, Result analysis. **Richard T.K. Wong:** Supervision, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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