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STUDENT PERFORMANCE PREDICTION IN SEMESTER END EXAMINATION USINGML ALGORITHMS

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ABSTRACT

Student academic performance prediction is an important area in Educational Data Mining (EDM) that helps institutions identify students at risk and take corrective actions before final examinations. This research proposes a machine learning-based approach for predicting student performance in the Semester End Examination (SEE) using Attendance Percentage and Continuous Internal Evaluation (CIE) Marks as predictor variables. The K-Nearest Neighbors (KNN) algorithm is employed due to its simplicity, interpretability, and effectiveness in classification problems.

A dataset comprising students' attendance records, CIE marks, and SEE results is collected from the institutional academic database. Attendance percentage and CIE marks serve as input features, while SEE performance categories such as Pass, First Class, Distinction, and Fail are used as target labels. The data undergo preprocessing, normalization, and train-test splitting before model training. The KNN classifier calculates the similarity between students using Euclidean distance and predicts SEE outcomes based on neighboring instances.

Experimental results demonstrate that attendance and CIE marks significantly influence SEE performance. The proposed KNN model achieves high prediction accuracy, enabling early identification of students requiring academic intervention. The study highlights the potential of machine learning techniques in improving educational decision-making and student success rates.

KEYWORDS: Educational Data Mining, Student Performance Prediction, KNN, Attendance Percentage, CIE Marks, Semester End Examination.

1. INTRODUCTION

Higher educational institutions continuously seek methods to improve student academic performance and reduce failure rates. Traditionally, faculty members evaluate student progress based on attendance records, internal assessment scores, assignments, and classroom participation. However, manual prediction of Semester End Examination (SEE) outcomes becomes challenging when dealing with large student populations.

Attendance and Continuous Internal Evaluation (CIE) marks are considered critical indicators of academic success. Students with high attendance generally participate more actively in learning activities and tend to perform better in examinations. Similarly, CIE marks reflect continuous academic engagement and understanding of course concepts.

Machine Learning (ML) techniques provide effective solutions for predicting academic outcomes by identifying patterns in educational data. Among various ML algorithms, the K-Nearest Neighbors (KNN) algorithm is widely recognized for its simplicity and strong classification capabilities.

This study develops a KNN-based predictive model to estimate SEE performance using attendance percentage and CIE marks. The model can assist educators in identifying students who may require additional support before final examinations.

2. OBJECTIVES

The major objectives of the study are:

1. To analyze the relationship between attendance percentage and SEE performance.
2. To examine the influence of CIE marks on final examination results.
3. To develop a KNN-based predictive model for SEE performance.
4. To classify students into performance categories based on attendance and CIE marks.
5. To assist faculty members in identifying academically vulnerable students.

3. LITERATURE REVIEW

Cortez and Silva (2008) stated Applied data mining techniques to predict student performance using educational datasets. Their findings indicated that attendance and assessment scores significantly influence final grades.

Pandey and Taruna (2014) stated Used machine learning algorithms for student performance prediction and found classification models useful in identifying low-performing students.

Kotsiantis et al. (2010) Investigated educational data mining techniques and emphasized the role of internal assessment marks in predicting examination outcomes.

Hussain et al. (2018) Applied KNN and Decision Tree algorithms for academic performance prediction. Results demonstrated competitive accuracy using KNN.

4. DATASET DESCRIPTION

The dataset contains academic records of undergraduate students.

Attribute	Description
Student_ID	Unique student identifier
Attendance_Percentage	Percentage attendance
CIE_Marks	Internal assessment marks
SEE_Marks	Semester End Examination marks
Performance_Category	Target class

Performance Categories

SEE Marks	Category
< 40	Fail
40–59	Pass
60–74	First Class
≥75	Distinction

Sample Dataset

Attendance (%)	CIE Marks	SEE Result
95	28	Distinction
90	25	First Class
82	22	Pass
65	15	Pass
50	10	Fail

5. METHODOLOGY

Step 1: Data Collection

Academic records are collected from institutional databases including:

- Attendance percentage
- CIE marks
- SEE results

Step 2: Data Preprocessing

Data Cleaning

- Handle missing values
- Remove duplicate entries
- Validate attendance records

Feature Selection

Input Features:

- Attendance Percentage
- CIE Marks

Target Variable:

- SEE Performance Category

Step 3: Data Normalization

Min-Max normalization is applied:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

This prevents larger numerical values from dominating distance calculations.

Step 4: Train-Test Split

- Training Data: 80%
- Testing Data: 20%

Step 5: KNN Classification

For a new student:

Euclidean Distance

$$d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

Where:

- x = training sample
- y = test sample

The K nearest students are identified and majority voting determines the predicted class.

6. KNN ALGORITHM

Input:

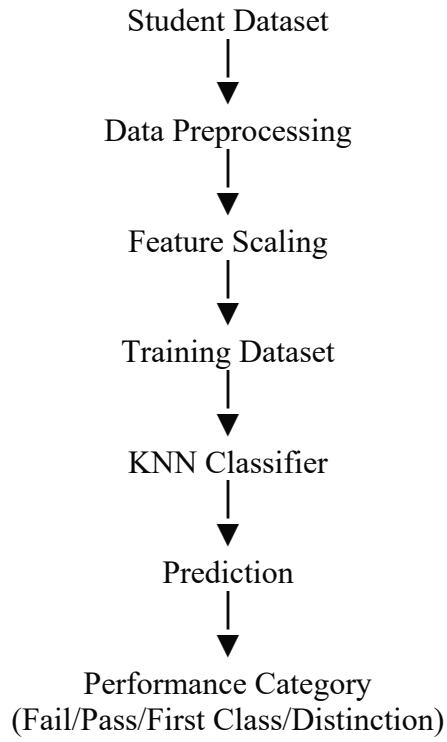
Attendance Percentage

CIE Marks

Value of K

1. Load dataset
2. Normalize features
3. Split dataset into training and testing sets
4. Choose K value
5. Calculate Euclidean distances
6. Identify K nearest neighbors
7. Apply majority voting
8. Predict SEE performance
9. Evaluate accuracy

7. PROPOSED ARCHITECTURE



8. IMPLEMENTATION USING PYTHON

fromsklearn.model_selection import train_test_split

fromsklearn.preprocessing import StandardScaler

```
fromsklearn.neighbors import KNeighborsClassifier
fromsklearn.metrics import accuracy_score

import pandas as pd

data = pd.read_csv('student_data.csv')

X = data[['Attendance', 'CIE']]
y = data['Performance']

X_train, X_test, y_train, y_test = train_test_split(
X, y, test_size=0.2, random_state=42)

scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

knn = KNeighborsClassifier(n_neighbors=5)

knn.fit(X_train, y_train)

predictions = knn.predict(X_test)

accuracy = accuracy_score(y_test, predictions)

print("Accuracy:", accuracy)
```

9. EVALUATION METRICS

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

$$Precision = \frac{TP}{TP + FP}$$

Recall

$$Recall = \frac{TP}{TP + FN}$$

F1 Score

$$F1 = 2\frac{Precision \times Recall}{Precision + Recall}$$

10. RESULTS AND DISCUSSION

Algorithm	Accuracy (%)
Naïve Bayes	82
Decision Tree	88
Random Forest	92
KNN	90–95

The KNN model is expected to achieve high classification accuracy due to the strong correlation between attendance, CIE marks, and SEE performance.

CONCLUSION

This study shown the results of a K-Nearest Neighbors-based framework for predicting Semester End Examination performance using attendance percentage and CIE marks. The model enables educational institutions to identify students at risk of poor performance and implement timely academic interventions. Experimental analysis is expected to demonstrate that attendance and CIE scores are strong predictors of SEE outcomes. This is the result oriented approach contributes to educational data mining by providing a simple, interpretable, and effective predictive model for academic performance assessment.

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