Student Adaptability Levels in Online Education

Sonya Melendez, Jordyn Geller, Kjorte Harra, Paulina Grekov, David Giardino

Background

- Covid-19 had led to a substantial increase in the use of online education across school-levels.
- Adaptability is a the ability to regulate behaviors, thoughts, and feelings in response to unexpected situations and circumstances (Martin, 2012).
- Interest in determining how students across different demographics adapt to virtual learning environments (Martin, 2021; Widikasih, 2021).

Research Questions

- What characteristics are relevant to categorize and predict students' adaptability to online education?
- What analysis techniques produce stronger, and more reliable, predictions?

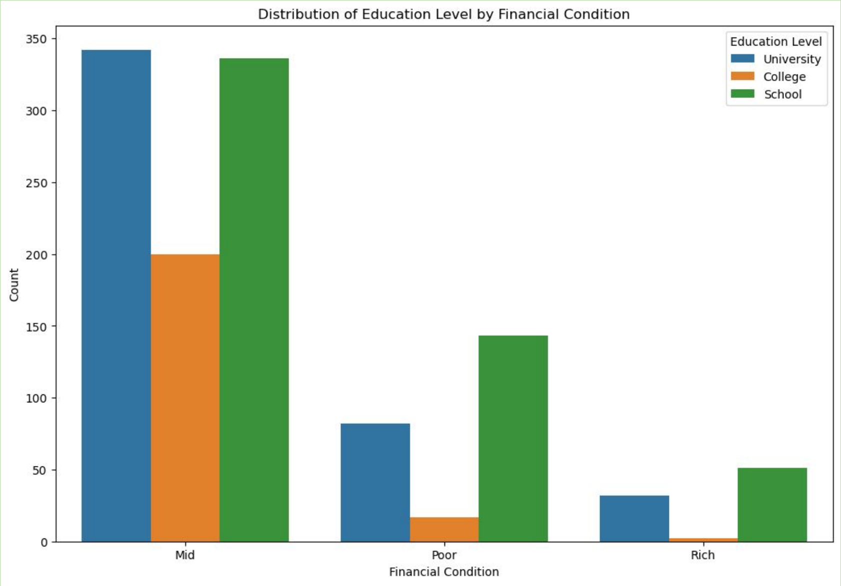
The Data

- Data originates from a 2021 Bangladeshi study investigating factors associated with student adaptability to online education (Suzan et al., 2021).
- Outcome variable of interest: student adaptability (low, moderate, or high).
- Predictor variables of interest: age group, student gender, and student financial status.
- Student data collected in online and offline surveys.

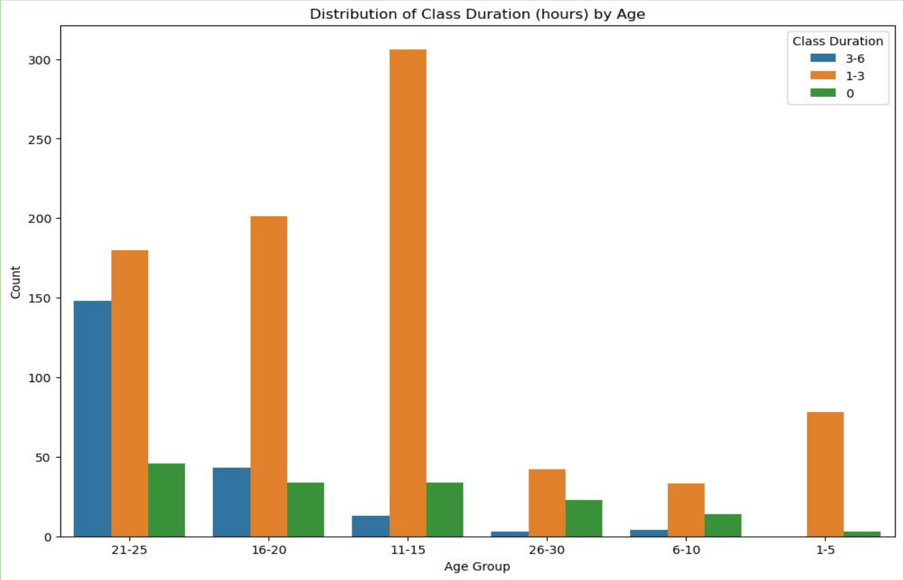
Methods

- Descriptive graphs to visualize and assess distributional characteristics of the dataset.
- Develop logistic regression, SVM, kNN, and decision trees aiming to predict a student’s adaptability to online education based on relevant predictors such as student class duration, age, and financial condition.
- Compare the accuracy of predictions of our models to determine the strongest model for the context.

Descriptive Graphs

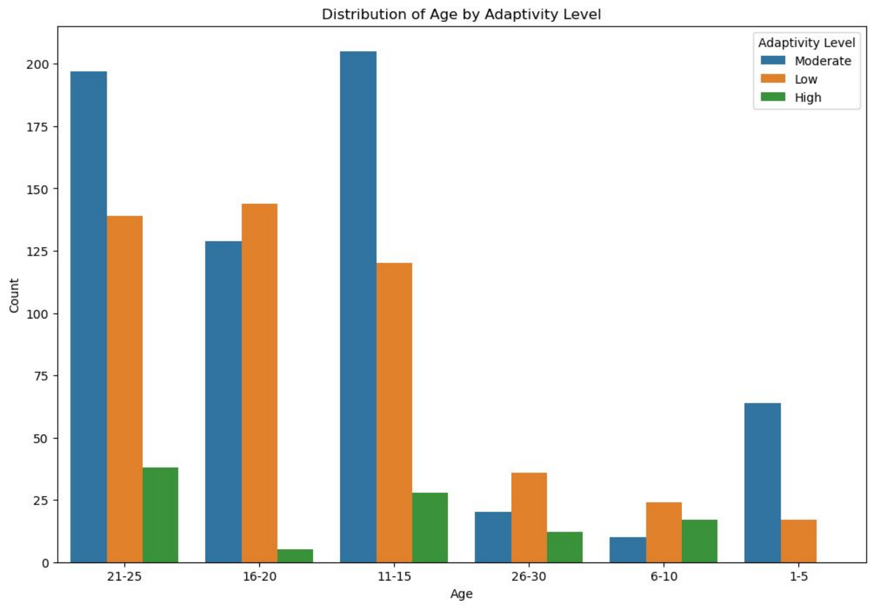


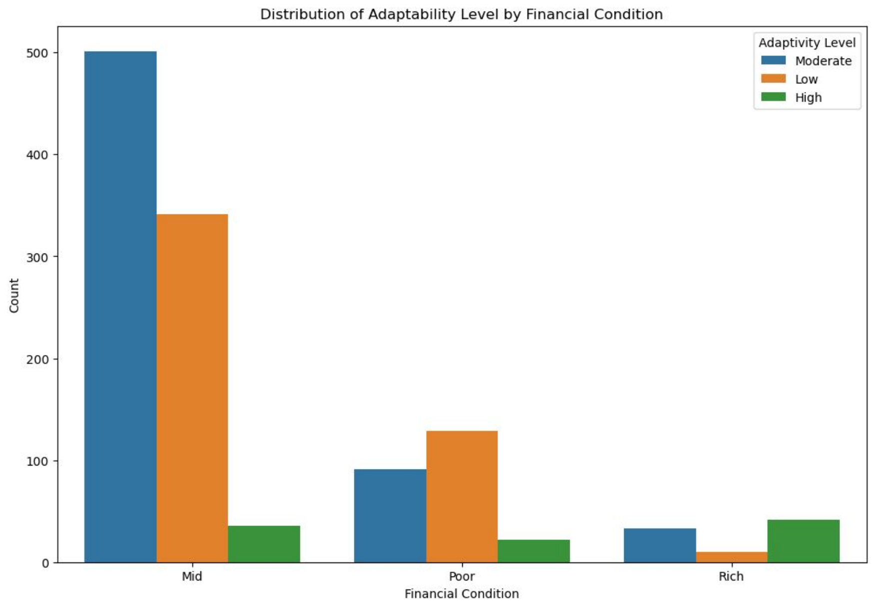
Illustrating the distribution of education levels across different financial conditions provides insight into how financial conditions vary within each education level.



Illustrating the distribution of class durations across different age groups allows us to observe patterns in the time spent in class based on age and allows us to discern potential age-related factors influencing class duration and potentially adaptivity.

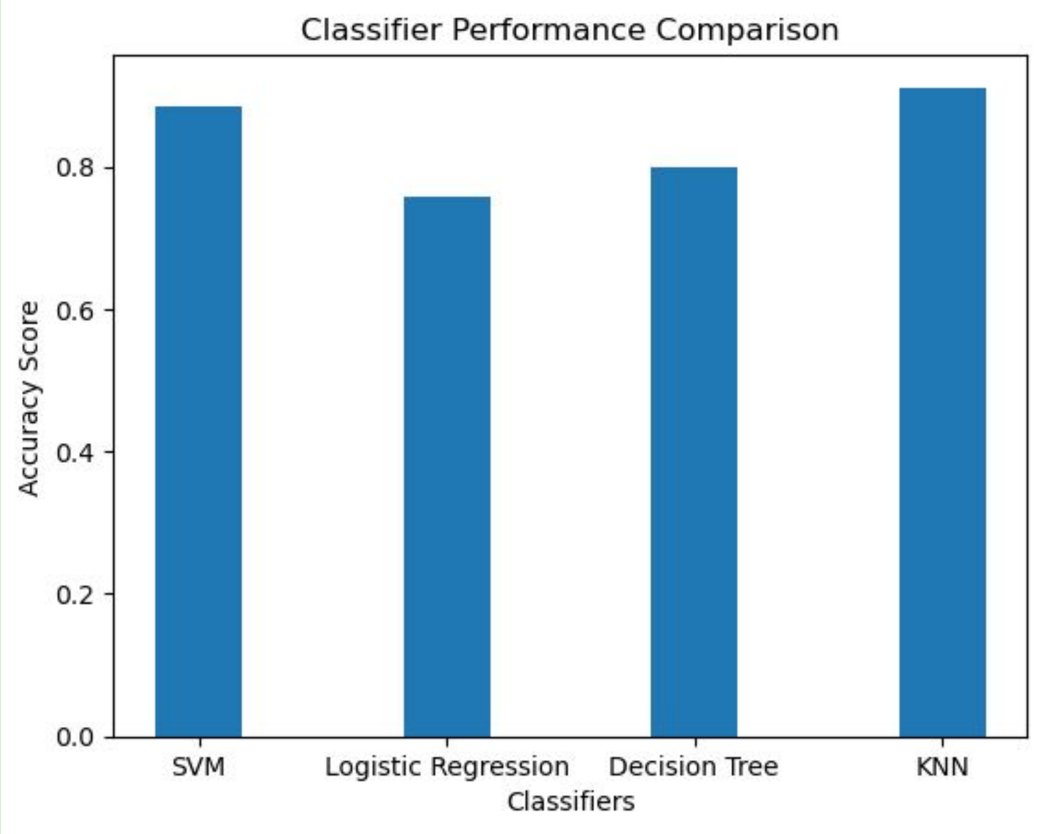
Descriptive Graphs





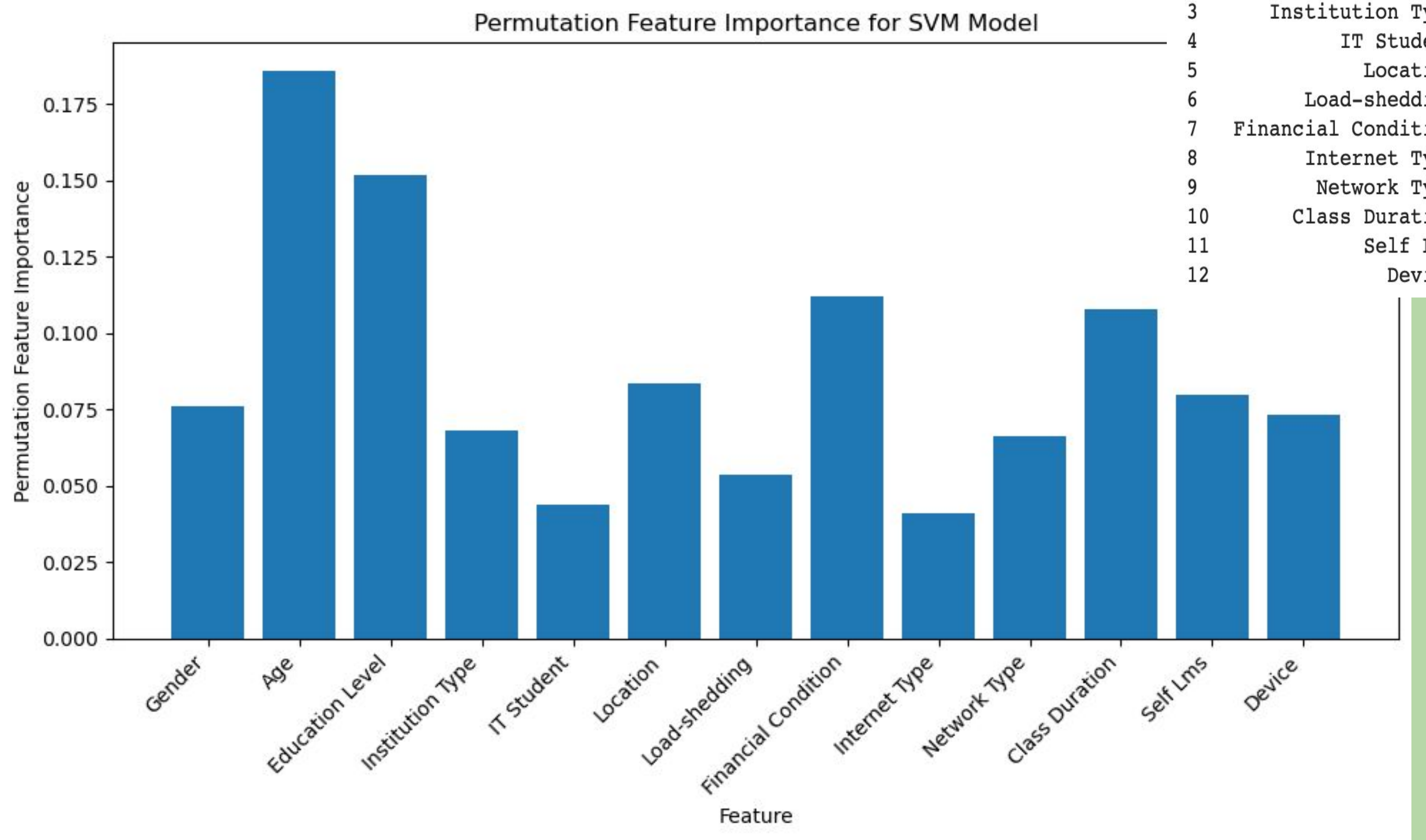
Illustrating the distribution of age groups within adaptivity levels showing how adaptivity levels vary across age groups which is essential for interpreting the impact of age on adaptability.

Illustrating the distribution of adaptivity levels in relation to financial conditions offers an understanding of how financial conditions can influence how kids are adapting..with more money come more opportunities and help.

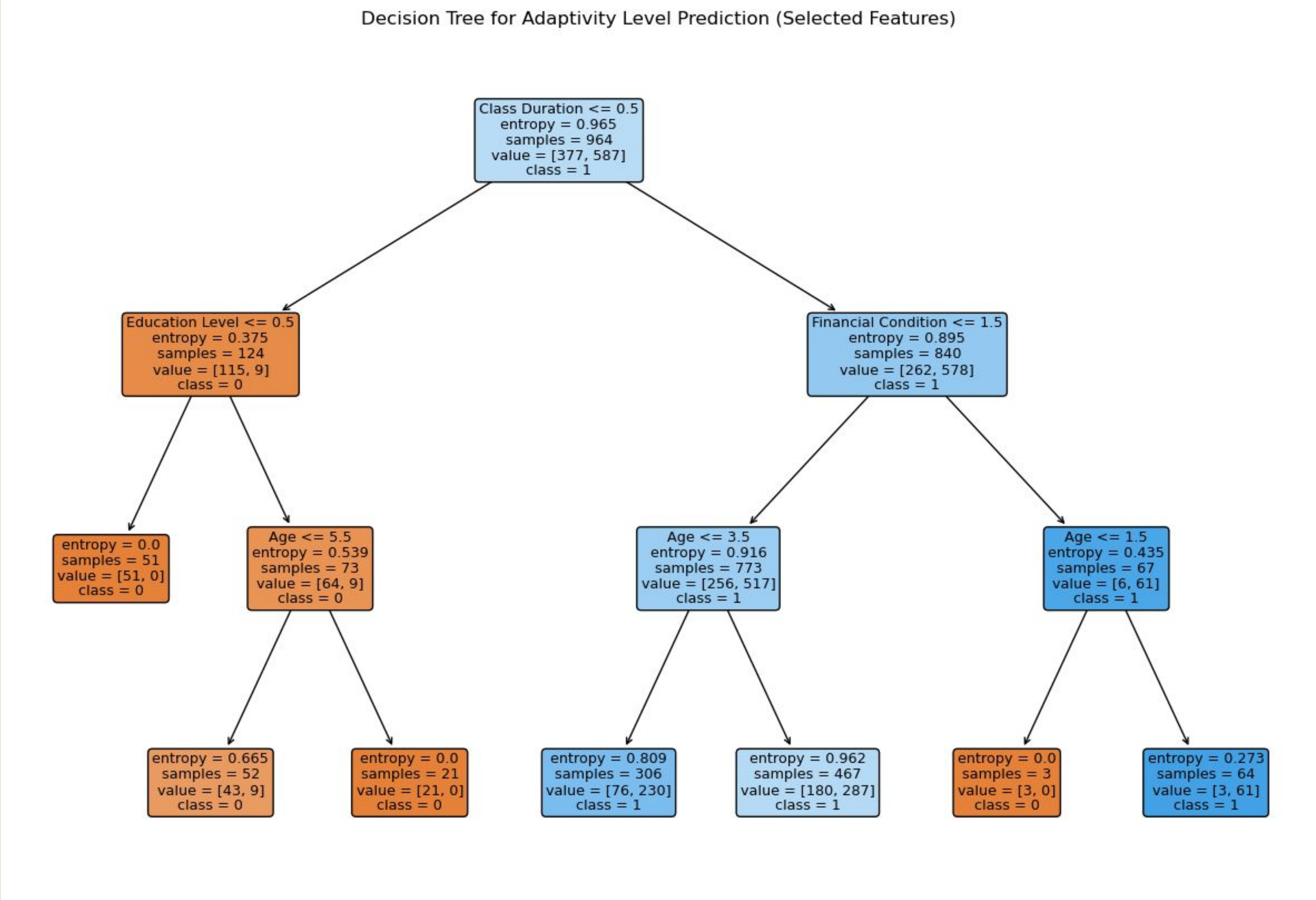


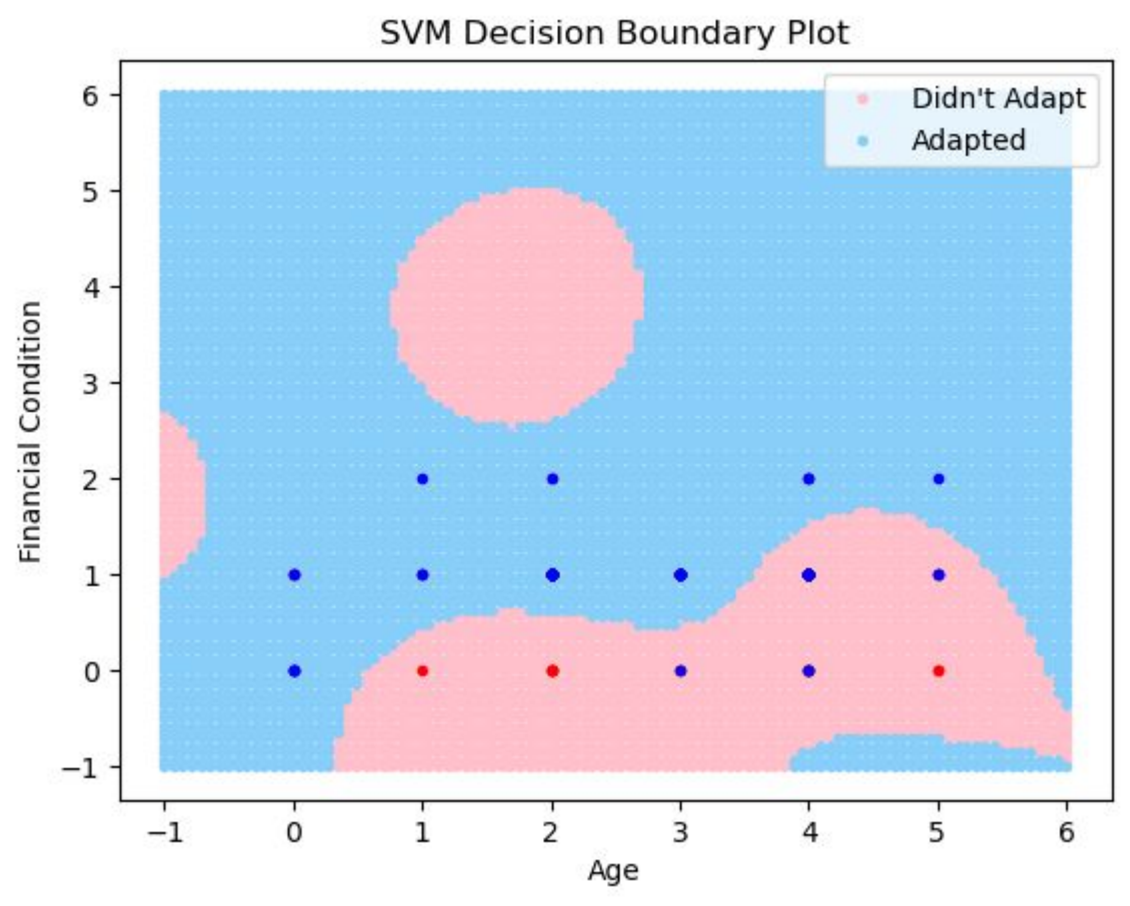
Based on the graph we made to determine which classifier was most useful we found that KNN was the best performing model on the validation data over all the features. We also found that Logistic Regression was the worst model, therefore we did not make any graphs because they would not have been helpful due to only having categorical variables.

```
Accuracy on the validation data 0 = SVM: 0.901
Accuracy on the validation data 1 = Logistic Regression: 0.757
Accuracy on the validation data 2 = Decision Tree: 0.802
Accuracy on the validation data 3 = KNN: 0.920
```

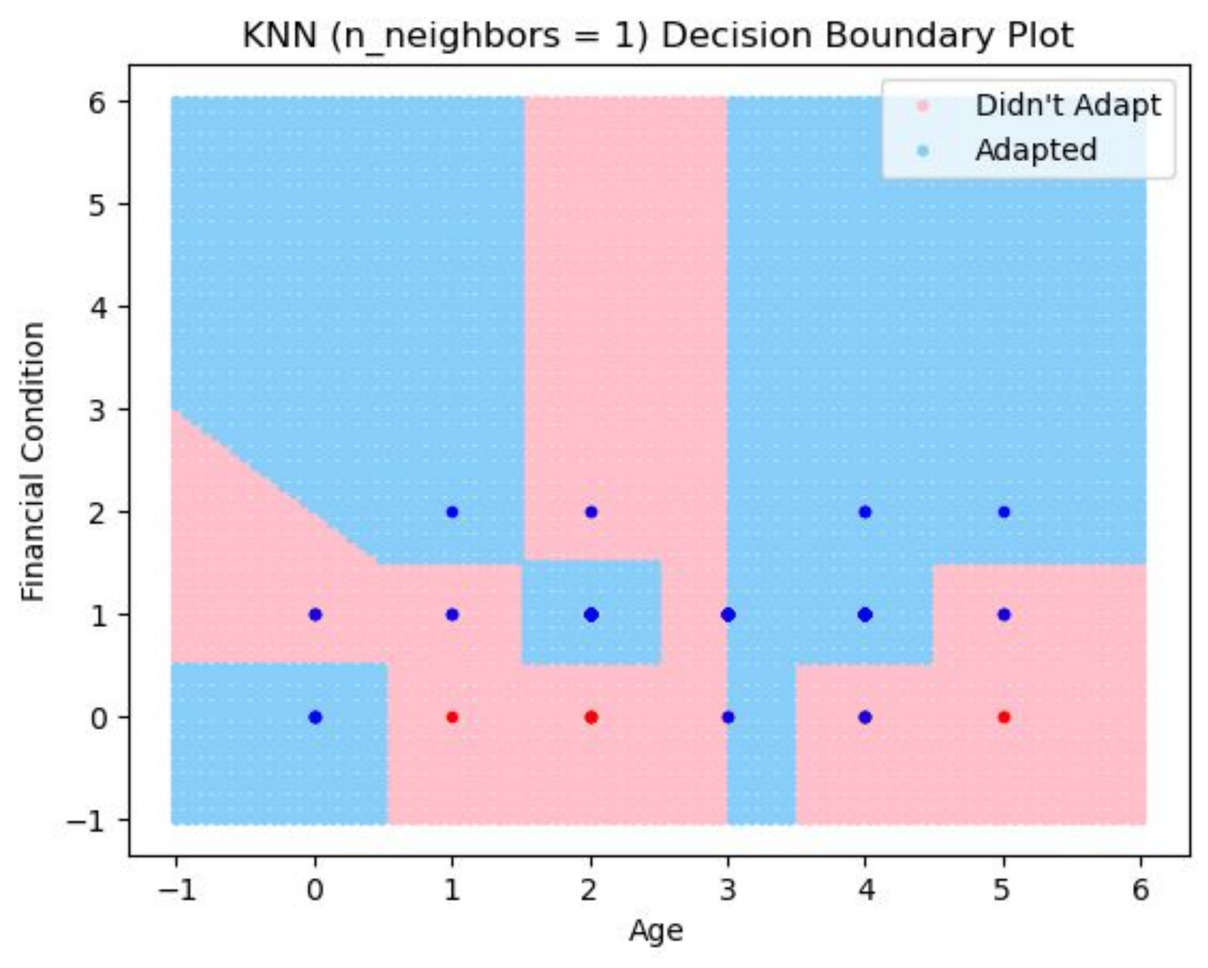


	Feature	Permutation Feature Importance
0	Gender	0.076033
1	Age	0.185675
2	Education Level	0.151791
3	Institution Type	0.068044
4	IT Student	0.043802
5	Location	0.083471
6	Load-shedding	0.053719
7	Financial Condition	0.111846
8	Internet Type	0.040771
9	Network Type	0.066391
10	Class Duration	0.107989
11	Self Lms	0.079614
12	Device	0.073003

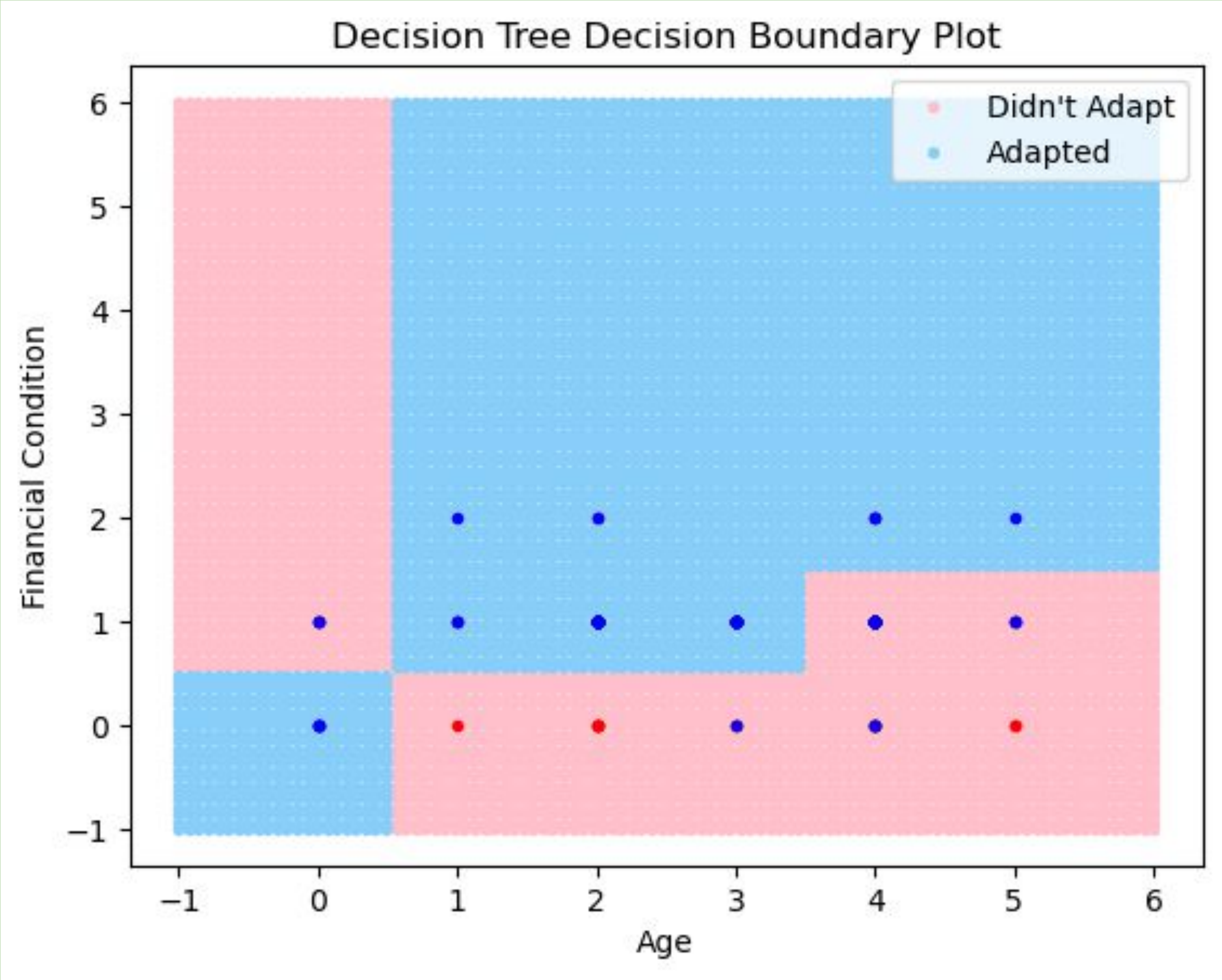

Decision Tree for Adaptivity Level Prediction (Selected Features)
Class Duration <= 0.5
entropy = 0.965
samples = 964
value = [377, 587]
class = 1
Education Level <= 0.5
entropy = 0.375
samples = 124
value = [115, 9]
class = 0
Financial Condition <= 1.5
entropy = 0.895
samples = 840
value = [262, 578]
class = 1
entropy = 0.0
samples = 51
value = [51, 0]
class = 0
Age <= 5.5
entropy = 0.539
samples = 73
value = [64, 9]
class = 0
Age <= 3.5
entropy = 0.916
samples = 773
value = [256, 517]
class = 1
Age <= 1.5
entropy = 0.435
samples = 67
value = [6, 61]
class = 1
entropy = 0.665
samples = 52
value = [43, 9]
class = 0
entropy = 0.0
samples = 21
value = [21, 0]
class = 0
entropy = 0.809
samples = 306
value = [76, 230]
class = 1
entropy = 0.962
samples = 467
value = [180, 287]
class = 1
entropy = 0.0
samples = 3
value = [3, 0]
class = 0
entropy = 0.273
samples = 64
value = [3, 61]
class = 1



The decision boundary shows the predicted adaptability level for combinations of different ages and financial conditions according to our SVM model on validation data with C = 100 and an rbf kernel.



The decision boundary shows the predicted adaptability level for combinations of different ages and financial conditions according to our KNN-Classifier model on validation data with number of neighbors at 1 because it was the best performing hyperparameter.



The decision boundary shows the predicted adaptability level for combinations of different ages and financial conditions according to our Decision Tree model on validation data with entropy criterion and max_depth at 3.

Conclusions

We found that in the context of our data kNN performed the best in terms of accurately predicting student adaptability overall. Age and financial status of students are the most important features for these predictions.

References

Martin, A. J., Collie, R. J., & Nagy, R. P. (2021). Adaptability and high school students' online learning during COVID-19. A job demands-resources perspective. *Frontiers in Psychology*, 12.

Martin, A. J., Nejad, H., Colmar, S., & Liem, G. A. D. (2012). Adaptability: Conceptual and empirical perspectives on responses to change, novelty and uncertainty. *Journal of Psychologists and Counsellors in Schools*, 22(1), 58-81.

Suzan, M. H., Samrin, N. A., Biswas, A. A., & Pramanik, A. (2021). Students' Adaptability Level Prediction in Online Education using Machine Learning Approaches. In *2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT)* (pp. 1-7). IEEE.

Widikasih, P. A., Widiana, I. W., & Margunayasa, I. G. (2021). Online learning problems for elementary school students. *Journal of Education Research and Evaluation,* 5(3), 489-497.

Data retrieved from: https://www.kaggle.com/datasets/mdmahmudulhasansuzan/students-adaptability-level-in-online-education