# AI based algorithms for teaching method selection: Using tandem learning in mathematics.

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## Abstract

### Background

The main objective of higher education institutions is to provide quality education to its students. One way to achieve this is is by introducing various teaching methods, one of which is tandem learning. Not everyone responds well to a one-size-fits-all method, and therefore, uncovering insights for predictive model selection tailored to individual students or classrooms becomes imperative for teaching institutions. The knowledge is hidden among the educational data set and is extractable through data mining techniques. The aim of this study was to evaluate the performance of machine learning algorithms for predicting student response to tandem learning.

### Methods

A sample of 89 high school students and 13 predictor variables has been used. The outcome of interest was a three state variable indicating whether the student responded well to implementation of tandem learning into education environment or not. In this paper, we implemented 9 classification machine learning algorithms that can be used to predict a target variable with three states and evaluated their performance with a 5 by 2-fold cross-validation with stratified folds.

### Results

Using all predictor variables, RF, KNN and GB performed best with accuracies 0.54, 0.53, 0.47 and macro F1 scores 0.37, 0.36, 0.33 respectively, which is fair considering data balance. Balancing the dataset and using only 2 outcome classes, performance was better, with best algorithm being GB, performing moderately well, having accuracy of 0.59 and F1-score of 0.59.

### Conclusion

The results imply that machine learning algorithms struggle to accurately predict students' responses to group learning in mathematics using the variables and sample size employed. As a result, they may not be appropriate for aiding teachers in making decisions about selecting teaching methods. Crucial insight that a simplified approach can yield more effective results is made from the transformation of the machine learning classification problem from three states to two.

### Keywords

Assessment, education, machine learning, tandem learning, data mining, teching methods

### Math subject classification, MSC2020

97D40, 97D60, 62P99

## Introduction and theoretical framework

### Teaching methods and tandem learning

/kratek povzetek članka variable\_importance o teoriji za učenje v skupinah/

### Machine learning and classification

Data mining is the process of uncovering hidden patterns, relationships, or insights within vast datasets through techniques from statistics and database management (Baradwaj & Pal, 2012). It involves data preprocessing to prepare information for analysis and utilizes methods such as clustering and association rule mining (Singhal & Jena, 2013). In contrast, machine learning, a subset of artificial intelligence, focuses on building predictive models by allowing computers to learn from data and make decisions or predictions (Candanedo et al., 2018). The sequences of steps identified in extracting knowledge from data is shown in Figure 2 below.

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Figure : Knowledge discovery process

Machine learning encompasses various learning paradigms, including classification process and finds applications in areas like recommendation systems. Classification, a fundamental task in both data mining and machine learning, involves categorizing data into predefined classes, such as binary or three-state classification, based on patterns learned from labeled data. This classification process is employed in various domains, such as healthcare and sentiment analysis, which includes educational sciences (Shaik et al., 2023), to make data-driven decisions (Baradwaj & Pal, 2012).

### Connecting tandem learning and machine learning

Technologies can be considered in terms of whether they are mainly student teaching (with primarily instructionist approach), student supporting (primarily constructivist approach), or teacher supporting (which primarily help teachers do tasks they already do but faster or with less effort) (Holmes et al., 2019).

Beyond its broader applications, machine learning has been harnessed to predict student performance with remarkable precision (Ofori et al., 2020; Qazdar et al., 2019; Rastrollo-Guerrero et al., 2020; Yakubu & Abubakar, 2022). Leveraging the power of data analytics and advanced algorithms, machine learning models have been applied to forecast student success (Yakubu & Abubakar, 2022), identify at-risk learners (Adnan et al., 2021; Chui et al., 2020), and tailor educational interventions (Luan & Tsai, 2021; Stimpson & Cummings, 2014; Tsai et al., 2020; Yang, 2021). This transformative application of machine learning is exemplified by research conducted by Siemens & Gasevic (2012), which introduced the concept of "learning analytics" and demonstrated its potential in predicting student outcomes, which was demonstrated also by other studies (Abana, 2019; Bhusal, 2021; Cortez & Silva, 2008; Kotsiantis et al., 2004; Minaei-Bidgoli et al., 2003). Aside from forecasting success, machine learning can help us identify the most important variables that affect said forecast (Lu et al., 2020; Luan & Tsai, 2021). Multiple studies have dvelved into the analysis of crucial features in learning enviroment (Hodges, 2018; Humphrey et al., 2009; Moradi et al., 2018; Scribner & Donaldson, 2001), however only few have harnessed the power of modern algorithms, such as machine learning, which hold the potential for significantly enhanced sight. Therefore, it is of paramount importance to explore in great detail the feature selection problem.

## Empirical work

Research was conducted as he effectiveness of tandem learning in high school mathematics remains unclear due to the complexity of numerous variables influencing its success.

This study aims to leverage three state classification machine learning algorithms to analyze multifaceted variables to determine successfulness of tandem learning enviroment.

Given the scarcity of comprehensive studies employing machine learning algorithms to assess teaching method selections, this research acknowledges the potential limitations in drawing definitive conclusions. While aiming to discern patterns of predicting successfulness of tandem learning enviroment, this study will consider the need for cautious interpretation of results. Even in the absence of conclusive findings, insights gathered from the analysis will contribute to the ongoing discourse on the efficacy of tandem learning in mathematics education. Therefore we hypothesize that even when feeding machine learning models with diverse data sets encompassing student profiles and collaborative dynamics some algorithms will perform sub par, while others may perform fair.

## Methodology

In the present research, the causal descriptive method of pedagogical research is applied.

## Sample

In this retrospective study we used a dataset gathered at a high school in Slovenia, which is pulicly available at (Bregant, 2023). Sample comprised of 89 11th and 12th grade of a Slovenian Gymnasium (i.e., high school); 28 males and 61 females. All variables provided were used. Internal consistency of a dataset was already performed at (Bregant et al., 2024), with McDonal's Omega for continuous data and Gutman's Lambda for categorical variables all of them having fair results.

## Data preprocessing and data analysis

The gathered data was analysed using Python programming language, primarily using pandas (version 2.1.3) and scikit-learn (version 1.3.2) libraries. Machine learning code, as well as variable importance and other data analysis notebooks are openly accessible at (Bregant, 2023)

Dataset was already in the form of tidy data (Wickham, 2014). Categorical variables, which were a priori encoded using label encoding were transformed into dummy variables using one-hot as most machine learning algorithms require numerical input and do not handle well numerical data, that is not continuous (Tan & Pu, 2023; Wu et al., 2020).

We implemented 9 ML algorithms: Naive Bayes, K-Nearest Neighbors, Decision Tree, Gaussian Mixture, Linear Discriminant Analysis, Ada Boots (with 1000 estimators), Gradient Boosting (with 1000 estimators), Support Vector Machine (with RBF kernel) and Random Forest (with 1000 estimators). Said algorithms are capable of performing 3 state classification. Models were evaluated using 5x2-CV with stratified folds with the main metric of performance evaluation being macro F1-score through average fold repetition.

## Results

### Student sample and variables used

Target variable was a three state measure of successfulness on Likert scale, both regarding academic performance as well as general wellbeing during implementation of tandem learning. general sense (gender, class, professor, previous grade,) in psychological sense (MBTI variables: extroversion-introversion, sensing-intuition, thinking-feeling and judging-perceiving and other variables: mathematical anxiety and motivation) and in regards to tandem learning (qualitative interaction, quantitative interaction and whether student outperformed their partner). For a more detailed and precise dataset description, refer to (Bregant et al., 2024) for comprehensive insights.

For machine learning purposes that follows it is important to know that target variable was not balanced with represented classes being 6, 39 and 44 respectively on Likert scale.

Feature importance was already performed by (Bregant et al., 2024), indicating that variables in regards to tandem learning are most important, followed by variables in general sense and lastly variables regarding psychological profile of students were least important.

A group of graphs with different colored bars

Description automatically generated with medium confidence

Figure : Variables used

### Model performance

According to F1 metric, the three models with generally better performances in our experiments were Random forest, K-Nearest Neighbors, and Gradient boosting. Their performance are fair, as their accuracy was still better than number of samples in biggest class (49.4%) Torej bolje od ugibanja. Other models performed worse, their poor performance indicating, they might not be learning the underlying patterns effectively. Whole classification table can be found in Table 1.

Table : Classification result.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Classifier | Accuracy | Precision\_macro | Recall\_macro | F1\_macro |
| Naive Bayes | 0.35 | 0.41 | 0.39 | 0.3 |
| K-Nearest Neighbors | 0.53 | 0.36 | 0.38 | 0.36 |
| Decision Tree | 0.4 | 0.31 | 0.29 | 0.28 |
| Gaussian Mixture | 0.01 | 0.0 | 0.07 | 0.01 |
| Linear Discriminant Analysis | 0.44 | 0.31 | 0.31 | 0.31 |
| AdaBoost | 0.39 | 0.27 | 0.28 | 0.27 |
| Gradient Boosting | 0.47 | 0.33 | 0.34 | 0.33 |
| Support Vector Machine | 0.45 | 0.16 | 0.3 | 0.21 |
| Random Forest | 0.54 | 0.37 | 0.38 | 0.37 |

In analyzing the model's performance, the plotted confusion matrices provide a visual representation of its classification accuracy, revealing the interplay between true positives, true negatives, false positives, and false negatives (Chicco et al., 2021).

Figure : Confusion matrices of classification.

A grid of blue squares

Description automatically generated

To counter the imbalance in our dataset, we opted for a binary approach, merging classes 0 and 1 to create a more balanced representation (Harangi et al., 2020). Therefore we got class 0 with 45 (50.6%) and class 1 with 44 (49.4%) representations. With this approach all algorithms, except GM and KNN performed fair. GB performed best, with moderate accuracy (0.59 averaged F1-score).

Table : Classification result of two classes... zamenjaj rezultate, saj so posodobljeni...

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Classifier | Accuracy | Precision\_macro | Recall\_macro | F1\_macro |
| Naive Bayes | 0.54 | 0.54 | 0.54 | 0.51 |
| K-Nearest Neighbors | 0.5 | 0.49 | 0.5 | 0.49 |
| Decision Tree | 0.53 | 0.53 | 0.52 | 0.52 |
| Gaussian Mixture | 0.51 | 0.45 | 0.5 | 0.45 |
| Linear Discriminant Analysis | 0.55 | 0.55 | 0.55 | 0.54 |
| AdaBoost | 0.55 | 0.55 | 0.55 | 0.54 |
| Gradient Boosting | 0.59 | 0.59 | 0.59 | 0.59 |
| Support Vector Machine | 0.58 | 0.59 | 0.58 | 0.56 |
| Random Forest | 0.54 | 0.54 | 0.54 | 0.53 |

A blue squares with white text

Description automatically generated

Figure : Confusion matrices for 2-state classification.

We also performed ML algorithms with less predictor variables, as discussed. We dropped all six variables regarding psychological profile of students in sample and achieved low performance on all algorithms mentioned above.

Table : Classification results with selected features

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Classifier | Accuracy | Precision | Recall | F1-score |
| Naive Bayes | 0.339 | 0.260 | 0.376 | 0.250 |
| K-Nearest Neighbors | 0.494 | 0.343 | 0.359 | 0.340 |
| Decision Tree | 0.449 | 0.330 | 0.323 | 0.310 |
| Gaussian Mixture | 0.033 | 0.016 | 0.142 | 0.027 |
| Linear Discriminant Analysis | 0.394 | 0.239 | 0.340 | 0.251 |
| AdaBoost | 0.359 | 0.252 | 0.263 | 0.250 |
| Gradient Boosting | 0.405 | 0.255 | 0.294 | 0.265 |
| Support Vector Machine | 0.495 | 0.165 | 0.333 | 0.221 |
| Random Forest | 0.494 | 0.301 | 0.359 | 0.315 |

Given the suboptimal performance of our model, we employed t-SNE analysis to visually explore and comprehend the underlying patterns and relationships within the data, aiming to uncover potential complexities or overlaps that might have impacted the model's performance (Bibal et al., 2023). It can be found in Appendix A, and shows that the patterns in data may be hard to distinguish between, as was speculated.

## Discussion

In this study, we used 9 ML algorithms to predict the success of tandem in three state of [tandem learning dataset](https://github.com/borbregant/ai_tandem_learning/blob/main/data_cleaned.xlsx), comprising of 89 students with 14 variables in various (continuous, categorical and ordinal) forms. Models performed poorly to fairly. Best accuracy and F1 score were achieved, when target variable was transformed into two states, however performance was still not the best. When taking variable importance into account, the model did also not improve.

The insights could contribute significantly to the development of tailored individual instructional strategies aimed at optimizing results and overall wellbeing during different teaching methods implementation. However, for implementation of results, we would like for the models to be more accurate and consistent, therefore more insight regarding variables used is needed for model improvement.

The application of supervised machine learning in predicting student response to tandem learning poses significant ethical challenges. While leveraging various general, psychological, and tandem learning-specific variables enhances predictive accuracy, it raises concerns regarding privacy, bias, and informed consent (Akgun & Greenhow, 2022; Starke et al., 2021). Collecting and analyzing personal data to predict individual behavior may compromise students' privacy, requiring strict adherence to data anonymization and consent protocols. Moreover, the inclusion of variables like cultural background or learning styles may inadvertently perpetuate biases or stereotypes (Marinucci et al., 2023). Transparency in model development, interpretability, and ongoing evaluation to mitigate biases remain pivotal.

## Conclusions and limitations

This study demonstrates that machine learning algorithms can be used for personalized predictive estimation of whether students respond well to new teaching methods. As using AI models is a fairly new construct, especially in education research, there is still a lot of room for improvement. Key factors that influence results must be investigated further to achieve better model outcomes. The potential incorporation of the developed model in regards to teacher assistance needs to be investigated further.

Study does not include a prediction whether tandem learning is overall effective or not. It simply includes information about predicting certain student performance, which is a limitation. Some of the variables, likely relevant (glej clanek variable importance) were not used in our models because they were not obtained, which might have led to a slight bias in our study,

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## Appendix A: t-SNE

A diagram of a graph

Description automatically generated with medium confidence

Figure : 2D t-SNE plot.

A diagram of a graph

Description automatically generated

Figure : 3D t-SNE plot.