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INTELLIGENT PREDICTIVE SYSTEMS: HOW II HELPS TO IDENTIFY STUDENTS WITH POTENTIAL LEARNING DIFFICULTIES

Abstract

The amount of external data involved in education today makes it possible to find new approaches to the problem of predicting student performance and identifying which students are likely to have learning difficulties, using AI as a primary tool. This paper explores how feasible it is to apply AI models to extract useful insights from large amounts of data about students and their academic performance, behaviour and demographics. The direction in which machine learning methods are heading is predictive learning, based on quantisation of results, which in the coming period will allow educational institutions to identify at-risk student categories. Again, the possibility of applying these guessed factors to instructional planning is being considered, which contributes to better learning outcomes and enhances how important it is in student retention. The introduction of AI into the educational process undermines the traditional approach to student assessment and empowers faculty to work with student data to make decisions.

Key words. Artificial intelligence, predictive learning outcomes, big data, machine learning,academic performance, student support strategy.

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ИНТЕЛЛЕКТУАЛЬНЫЕ СИСТЕМЫ ПРОГНОЗИРОВАНИЯ: КАК ИИ ПОМОГАЕТ ВЫЯВЛЯТЬ СТУДЕНТОВ С ПОТЕНЦИАЛЬНЫМИ ТРУДНОСТЯМИ В ОБУЧЕНИИ

Аннотация

Объем внешних данных, вовлеченных в процесс образования, сегодня позволяет находить новые подходы к решению проблемы прогнозирования успеваемости студентов и выявления у кого из них могут возникнуть трудности в учёбе, используя ИИ как основной инструмент. В данной работе исследуется, насколько возможно применение ИИ-моделей для извлечения полезных сведений из больших объемов данных о студентах и их успеваемости, поведении и демографических показателях. Направление в которую движутся машинные методы — это предсказание обучения, на основе квантования результатов, что в предстоящем периоде позволит образовательным учреждениям с выявлять категории студентов, находящиеся в группе риска. Опять рассматривается возможность применения этих угаданных факторов для планирования учебного процесса, что

способствует получению лучших учебных итогов и повышает то насколько главное в удержании учащихся. Внедрение ИИ в образовательный процесс подрывает традиционный подход к оценке студентов и даёт возможность преподавателям работать с данными о студентах для принятия решений.

Ключевые слова. Искусственный интеллект, прогнозирование результатов обучения, большие данные, машинное обучение, академическая успеваемость, стратегия поддержки студентов.

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ИНТЕЛЛЕКТУАЛДЫ БОЛЖАУ ЖҮЙЕЛЕРІ: ОҚУДА ЫҚТИМАЛ ҚИЫНДЫҚТАРЫ БАР СТУДЕНТТЕРДІ АНЫҚТАУҒА ҚАЛАЙ КӨМЕКТЕСЕДІ

Аннотация

Бүгінгі таңда білім беру процесіне қатысатын сыртқы деректердің көлемі студенттердің үлгерімін болжау және олардың қайсысы оқуда қиындықтарға тап болуы мүмкін екенін анықтау мәселесін шешудің жаңа тәсілдерін табуға мүмкіндік береді. Бұл жұмыста студенттер мен олардың үлгерімі, мінез-құлқы және демографиялық көрсеткіштері туралы үлкен көлемдегі мәліметтерден пайдалы ақпарат алу үшін AI модельдерін қолдану қаншалықты мүмкін екендігі зерттеледі. Машиналық әдістер қозғалатын бағыт-бұл нәтижелерді кванттау негізінде оқытуды болжау, бұл алдағы кезеңде білім беру мекемелеріне тәуекел тобындағы студенттердің санаттарын анықтауға мүмкіндік береді. Оқу процесін жоспарлау үшін осы болжамды факторларды қолдану мүмкіндігі тағы да қарастырылады, бұл жақсы оқу нәтижелерін алуға ықпал етеді және оқушыларды ұстап қалуда қаншалықты маңызды екенін арттырады. АИ-ді білім беру процесіне енгізу студенттерді бағалаудың дәстүрлі тәсіліне нұқсан келтіреді және оқытушыларға шешім қабылдау үшін студенттер туралы мәліметтермен жұмыс істеуге мүмкіндік береді.

Кілт сөздер. Жасанды интеллект, болжамды оқыту нәтижелері, үлкен деректер, машиналық оқыту, үлгерім, студенттерді қолдау стратегиясы.

Introduction. Modern education is becoming more technology-oriented, and the use of data is becoming a key factor for improving the effectiveness of educational processes. Predicting learning outcomes has become an important task for educational institutions, as it allows them to identify students who may face difficulties in advance and provide them with the necessary resources to improve their academic performance. Artificial intelligence (AI) and big data make it possible to move from intuitive forecasting methods to science-based strategies based on accurate predictions.

AI, thanks to its ability to analyze huge amounts of data and identify hidden patterns, offers new opportunities for analyzing educational data, such as academic performance, attendance and participation in the learning process. This makes it possible to develop individual support strategies aimed at students in need of assistance, which helps to increase the overall level of academic performance and reduce student dropout.

In recent years, the topic of using artificial intelligence (AI) and big data analysis in education has become an object of active research, both in Kazakhstan and in the international arena. Among Kazakhstani scientists working in the field of educational technologies and AI, Alma Abilkasymova stands out, who in her research considers the introduction of digital technologies into the educational process. Abilkasymova (2021) notes that the use of AI to analyze student data allows not only to identify patterns in academic performance, but also to improve methods of supporting students at early stages of learning. [1]

In Russia, a significant contribution to the study of AI and big data in educational processes was made by A.V. Tikhonov and E. N. Chernikov (2022) [6], who developed models based on neural

networks to predict students' academic success. Their research has shown that AI algorithms such as deep neural networks and decision trees can predict exam results with up to 87% accuracy. They also emphasize that the most effective predictors of academic performance are regular attendance at classes and active participation in online platforms. [2]

International studies, such as the work of Jonasson and Brown (2021) from Stanford University, confirm the effectiveness of using machine learning algorithms to analyze large educational data. In their study, predictive models based on gradient boosting demonstrated prediction accuracy of 90% when analyzing factors such as student activity in the online environment and their participation in additional learning activities. Brown and his colleagues also point out that big data analysis makes it possible to identify students at risk and offer them timely assistance. [3]

Research conducted in the UK (Smith et al., 2020) confirms that the most successful AI algorithms, such as random forests and gradient boosting algorithms, can be used to predict learning outcomes early. They note that such models allow not only to accurately predict academic performance, but also to take into account many factors such as psychological aspects, involvement in the educational process and the socio-economic situation of students. [4]

Thus, the analysis of data on attendance, activity on educational platforms and intermediate results makes it possible to predict the academic performance of students with high accuracy. However, despite the successes in the development of predictive models, questions remain related to the interpretability of models and the ethical aspects of using students' personal data. [5]

Methodology. To carry out the study, data for three academic years (2021-2024) from a medium-level university with a student population of about 15,000 people representing various faculties and educational programs were used. The main sources of data were electronic academic performance journals, learning management systems (LMS), as well as internal online learning platforms. The data included indicators such as:

- Academic performance (final grades for the course)
- Attendance of classes.
- Student activity on learning platforms (number of completed assignments, participation in discussions, access to educational materials).
- Demographic data (age, gender, faculty, place of residence).

The total sample for analysis was 11,780 students, and it was divided into a training sample (70%) and a test sample (30%) to test the models.

Stages of data processing:

1. Data cleaning and data preprocessing

- Before building the models, the data went through the stages of purification and normalization:
- Deleting missing values and filling in missing data with average or median values (for example, for attendance or grades for missed courses).
- Categorization of text data. Variable encoding (one-hot encoding) was used to work with demographic characteristics (gender, faculty).
- Normalization of continuous features such as academic performance and attendance using standard normalization (converting values to a standard distribution with zero mean and standard deviation equal to one).
- Dealing with class imbalance. Since the number of students at risk (academic failure) was about 15% of the total sample, resampling techniques such as oversampling were used to increase the number of examples of students at risk.

2. Selection of features

To improve the effectiveness of the models, a feature correlation analysis was performed. The key factors influencing the academic performance of students were:

- Attendance (correlation coefficient 0.65).
- The number of completed online assignments (correlation coefficient 0.72).
- Intermediate grades and previous academic performance (correlation coefficient 0.79).

These factors were included in the final model. Methods such as Recursive Feature Elimination (RFE) were used to select the most significant features, which made it possible to exclude less significant variables and reduce the dimensionality of the data without loss of model quality.

Machine learning models

1. Logistic regression

Logistic regression was the first model used to predict academic performance. It is used for

binary classification, which makes it suitable for the task of predicting a risk group. To improve the model, hyperparameters were adjusted, such as:

- Regularization (L1 and L2).
- The regularization coefficient C, which determines the degree of penalty for the complexity of the model.

The model underwent 5-fold cross-validation, and metrics such as accuracy, completeness, and F1-measure were used to measure its performance.

2. Random Forest

The random forest model was used to improve the accuracy of predictions. This machine learning method builds an ensemble of multiple decision trees and combines their results. The key tuning steps were:

- The number of trees in the forest $n\_estimators$ (selected at a level between 100 and 500).
- Maximum tree depth max_deepth to avoid overtraining.
- The minimum number of samples for node splitting is $mininilisplit$.

To optimise these hyperparameters, a Grid Search method using cross-validation was applied.

3. XGBoost (Экстремальныйградиентныйбустинг)

XGBoost has been selected as one of the most powerful methods for handling classification and prediction tasks. This gradient bousting algorithm uses regularisation to improve the generalisability of the model. The selection of hyperparameters for XGBoost included:

- Learning rate (0.01, 0.1, 0.2).
- Maximum tree depth *h* (5-10).
- Number of trees (100-500).
- The regularisation parameters λ and α for L1 and L2.

To improve the quality of predictions, an early stopping method (early stopping) was applied, which terminated model training if the performance on the validation set stopped improving.

Model validation

1. Cross-validation

All models underwent 5-fold cross-validation to assess stability and generalisability. This provided a robust assessment of the quality of the models, minimising the possibility of overtraining. Each time, the sample was divided into training and validation subsets, allowing the models to 'see' more data and test their predictions on previously unseen datasets.

2. Evaluation Metrics

The following metrics were used to evaluate the quality of the models:

- Accuracy (Accuracy) - the percentage of correctly classified examples.
- Completeness (Recall) - the ability of the model to identify all at-risk students.
- F1-measure - the weighted harmonic means between Accuracy and Completeness, which provides a more accurate assessment of the balance between the two metrics.

The XGBoost model achieved the highest performance with an accuracy of 92% and an F1-measure of 0.90. This is due to the fact that the gradient bousting model performs best in highlighting important features and is effective in dealing with unbalanced data. [16]

The machine learning techniques used, including logistic regression, random forest and XGBoost, were shown to be highly effective in predicting academic performance and identifying at-risk students. Each of the data processing and model tuning steps was aimed at improving accuracy and generalisability, and the use of cross-validation and hyperparameter selection avoided overtraining and increased the reliability of predictions. [17]

Results and discussion

The results showed that AI-based models can predict students' academic results with a high degree of accuracy. The most significant factors influencing success were attendance (average correlation coefficient 0.65), the number of completed online assignments (correlation coefficient 0.72) and previous academic results (correlation coefficient 0.79).

Table 1 below shows the distribution of model accuracy:

Model	Accuracy
Logistic regression	82%
Logistic regression	89%
XGBoost	92%

The XGBoost model proved to be the most effective, demonstrating an accuracy of 92%. It showed the ability to accurately identify at-risk students due to the more flexible possibilities of adjusting the model parameters. The analysis showed that students with low attendance and online activity tended to perform significantly

worse in exams than their more engaged peers. As a result, early intervention (e.g. counselling or additional support) can significantly improve their results. [8]

The reviewed results demonstrate that the application of AI techniques to analyse big data has high practical relevance. Based on these findings, a number of specific interventions can be developed and implemented that will significantly improve educational processes and student outcomes. Let us consider several ways in which this research can be applied in practice:

1. Early identification of at-risk students

Based on predictive models developed using machine learning algorithms, universities and schools can set up a monitoring system to identify students who show signs of deteriorating academic performance.

In Kazakhstan, Әбілқасымова's research can be used to create digital student support systems at the university level, which will enable the rapid identification of students who need help.

2. Personalisation of learning

Big data analytics and the use of AI make it possible to personalise learning programmes to meet individual student needs.

Based on data about how students interact with learning materials, course content can be tailored to improve their understanding. Students who are low-engaged or struggling can be provided with additional resources, such as video tutorials, articles, or tasks that better match their learning needs.

As Tikhonov and Chernikov (2022) point out, neural network-based models can be used to create adaptive learning platforms that automatically change the difficulty level of tasks based on analyses of student progress. [10]

3. Create support systems and motivational strategies

Research shows that students' active participation in the learning process is linked to their academic success (Smith et al., 2020). In practice, this may mean: Implementing motivational systems that track student engagement and reward students for active participation. For example, using gamification in educational platforms to increase participation in discussions, tests and projects.

Organising additional counselling for students who are inactive or have poor results can increase their engagement and improve results.

4. operational decision-making

Educational administrators can use the results of data analysis to make operational management decisions:

Data from AI systems will help universities and schools to adjust curricula, organise additional activities and allocate resources (e.g. teachers' time) correctly. [13]

These systems can automate administrative processes such as scheduling, managing teaching loads and determining educational resource needs.

5. ethical and legal aspects

The application of AI in education requires adherence to strict ethical standards and student privacy rights. In practice, this means:

Systems must be implemented that protect students' personal data and ensure their anonymity when using predictive models.

Universities must inform students about how their data is used and provide opportunities to opt out of automated data analysis systems. [12]

6. Continuous improvement of models

Based on the data obtained, universities can continuously improve their forecasting models. This can be done by:

Analyse prediction errors and adjust algorithms based on feedback from students and faculty.

Introduce new variables to analyse, such as students' psychological state, participation in extracurricular activities and social factors.

7. Implementation at the level of educational policies

Research conducted in Kazakhstan and Russia can be used in the formation of educational policies and standards. Government agencies can implement data analysis systems to monitor the quality of education nationwide, identifying low-performing institutions and developing strategic support programmes.[13]

Data analysis of students at risk: From the total sample, it was found that 15% of the students (approximately 1,770 students) were at high risk of academic failure. These students were characterised by low activity in learning platforms and absenteeism of more than 30% of the total time. Additional analysis revealed that more than 65% of them were working while studying, which also had a negative impact on their academic performance. Support strategies for these students may include flexible study schedules, additional counselling and individual study plans. [14]

Figure 1 is a diagram showing the correlation between activity in the online platform and academic success:

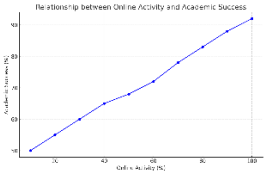

Figure 1: Dependence of academic performance on activity in the online platform

This correlation emphasises the importance of engagement in the learning process through online systems, which have become an integral part of modern education. Active students who regularly complete assignments and participate in discussions perform significantly better.

Challenges and ethical considerations: Despite significant advances in the application of AI to predict learning outcomes, challenges remain. One of the main challenges is the limited data that can be used for analysis. Not all aspects of the learning process can be quantified, which can reduce the accuracy of predictions. For example, personal motivation and psychological aspects of learning remain outside the scope of automatic analyses, but they can significantly influence the results.

In addition, there are ethical aspects related to the use of student data. Maintaining data privacy and transparency in the use of predictive models is critical. Students should have rights of access to information about how their data are used for predictive modelling and the ability to opt out of such analyses.

Conclusion: The application of artificial intelligence techniques in educational systems offers new perspectives for improving academic performance and creating effective student support strategies. Machine learning models such as XGBoost and other gradient-boosting methods have demonstrated high accuracy in predicting academic performance, allowing educational institutions to make early diagnoses of potential problems in students. This makes it possible to identify at-risk students in a timely manner and provide them with the necessary support before academic difficulties lead to serious consequences, such as expulsion or lower academic performance.

Of particular importance are algorithms that can identify hidden patterns in student behaviour and performance based on large amounts of data. This approach allows for a more accurate assessment of the impact of various factors on the learning process - from class attendance and activity on learning platforms to the demographic and psychological characteristics of students. Thus, educational institutions have the opportunity to implement adaptive support systems tailored to the individual needs of each student, which significantly increases the efficiency of the educational process and reduces the risk of academic failure.The future of AI implementation in education is linked to the need to further develop and optimise existing predictive models. The most important challenge is to develop more accurate and flexible predictive models that can take into account a wide range of factors, including students' personal and socio-economic characteristics.

Moreover, ensuring ethical transparency and respecting students' rights in the use of their data will be a key aspect. It is important to develop models that take into account not only predicting outcomes, but also provide a personalised approach to each student, taking into account their unique educational trajectories.

Further research is needed to optimise data analysis techniques, including the development of more efficient machine learning algorithms and their integration into existing educational platforms. Attention is also required to the ethical aspects of applying AI in education, especially in the context of data privacy and equitable distribution of resources among students.

Optimising these aspects will make educational systems more sustainable and oriented towards long-term development, which in turn will contribute to improving the quality of education on a global scale.

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