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The Use of Neural Networks for Predicting Student Academic Performance in Higher Education

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***Abstract.** This paper investigates the use of neural networks to predict student academic performance in higher education. A hybrid CNN-LSTM model was developed to process temporal data on class attendance and online activity. The dataset included records of 1,200 students with exam scores, attendance, LMS engagement, and demographic data. Preprocessing involved cleaning, one-hot encoding, and Z-score normalization. The model achieved high prediction accuracy (MSE = 0.15, R^2 = 0.82), outperforming linear regression. For identifying at-risk students, the model reached a ROC-AUC of 0.88. The findings are valuable for the development of early warning systems in higher education institutions that enable the timely identification of students at risk.*

***Keywords:** neural networks, student performance prediction, hybrid CNN-LSTM architecture, educational machine learning, learning management system (LMS), anonymized academic data.*

Introduction

In recent years, higher education institutions have increasingly faced the need to promptly and accurately predict students' academic performance. Early identification of students experiencing academic difficulties enables instructors and support services to implement timely interventions, such as supplemental instruction, academic advising, and curriculum adjustments. Traditional statistical methods, such as linear regression or decision trees, often fall short in capturing the complex, high-dimensional relationships between academic outcomes, attendance, and activity within learning management systems [1; 2].

Neural networks, capable of uncovering hidden patterns in large volumes of heterogeneous data, represent a promising tool for tackling the problem of academic performance prediction. This study proposes a hybrid model that combines convolutional and recurrent blocks (CNN-LSTM) based on an anonymized dataset of undergraduate students from a technical university. This architecture enables not only the prediction of final grade point averages but also the identification of "at-risk" students who may require additional academic support. The following sections describe the stages of data preprocessing, model development, and performance evaluation.

Research Objective

The objective of this study is to develop and evaluate a hybrid CNN-LSTM model for accurately predicting the academic performance of students at a technical university and for the early identification of students at academic risk.

Research Tasks

- To collect and describe an anonymized academic dataset covering three semesters;
- To implement and train a hybrid neural network architecture;
- To assess the performance of the proposed model and compare it with traditional methods;
- To analyze the impact of key features on prediction accuracy;
- To develop practical recommendations for implementing the system within academic support services.

Neural networks, capable of detecting hidden patterns in large volumes of heterogeneous data, offer a promising approach to the challenge of academic performance prediction. This study proposes a hybrid model that combines convolutional and recurrent blocks (CNN-LSTM) based on an anonymized dataset of undergraduate students from a technical university. This architecture enables not only to predict the final grade point average but also to identify "at-risk" students who may require additional academic attention.

Prior work has progressed from interpretable but capacity-limited classical models to deep and explainable approaches. Early studies showed that linear regression and decision trees provide transparent baselines yet fail to capture complex nonlinear relations among behavioral and academic features [1]. Multilayer perceptrons modestly improved classification of "successful/at-risk" students (≈75% accuracy) but could not model temporal dependencies in activity data [3,4]. Deep hybrid architectures addressed this gap: CNN–LSTM models more effectively captured attendance and LMS dynamics, reaching ROC–AUC above 0.85 [5]. Beyond sequence modeling, graph neural networks that encode "student-student" and "student-course" relations further improved dropout-risk predictions, while explainable techniques such as LIME and SHAP clarified feature and edge contributions to increase practitioner trust [6,7]. In parallel, the gamification literature and mobile implementations indicate that points and badges can boost engagement–by about 30% in one study–and strengthen predictive signals available to performance models [8-10]. Recent surveys consolidate these advances, covering ensemble and deep methods and underscoring the role of transparency, with demonstrations of LIME/SHAP in higher-education contexts [11-13].

Taken together, contemporary research indicates that transitioning from classical methods to hybrid neural architectures and graph networks, along with incorporating gamification and mobile activity features, significantly improves the accuracy of academic performance prediction. At the same time, more complex models require extensive, well-prepared datasets and careful hyperparameter tuning.

Methodology

This study utilized anonymized data from 1,200 undergraduate students at a technical university, collected over three semesters. The dataset included four groups of features: academic performance (scores from quizzes and final exams), attendance (proportion of absences per course), online activity (number of lectures viewed, forum participation, and quiz submissions in the LMS), and socio-demographic parameters (student gender and field of study).

Figure 1 illustrates the distribution of students' average grades: most values are concentrated in the range of 2.5 to 3.5, with a slight skew towards higher grades. Small peaks around 2.8 and 3.2 indicate the most frequently occurring scores. The tails of the histogram reflect a few students with very low (below 2.0) and very high (above 4.0) performance.

Standard preprocessing was performed before training. Records with less than 60% feature completeness were removed to avoid bias from missing data. Categorical variables — gender and field of study — were one-hot encoded for proper network interpretation. Quantitative features (grades, attendance, activity) were standardized using semester-level Z-score normalization to align distributions

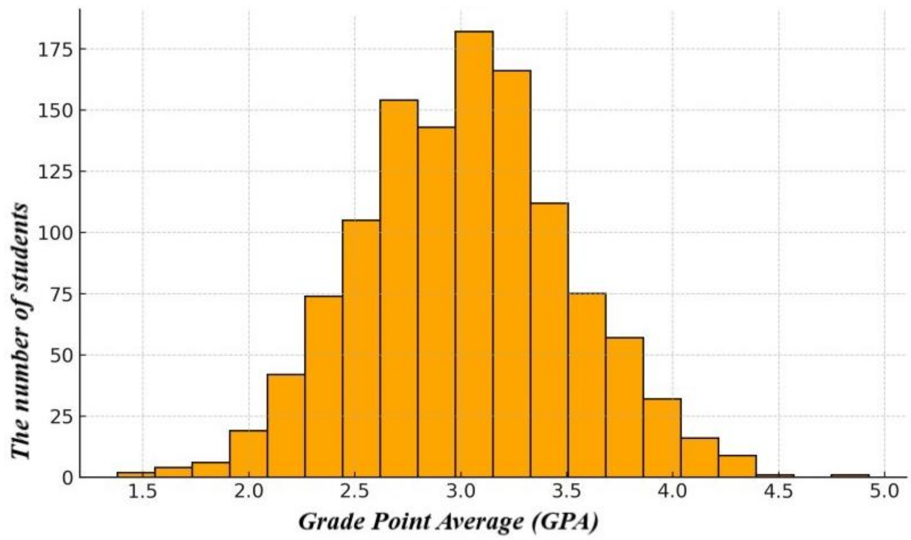

Figure 1 — Distribution of students' average grades

and mitigate outliers. Finally, the dataset was randomly split into training (70%), validation (15%), and test (15%) sets.

A hybrid architecture combining convolutional and recurrent components was proposed to predict the final average grade and identify students in the "at-risk" group. First, the student's "activity map" — a matrix of time × activity types — is processed by a convolutional block that extracts local behavior patterns, such as sharp changes in engagement during different periods of the semester. Then, the sequence of extracted features is passed to an LSTM block, which captures the temporal dynamics of the indicators throughout the semester. Finally, a fully connected layer integrates the extracted features and outputs the predicted average grade.

All model hyperparameters — including the number of convolutional filters, the LSTM hidden state size, and the learning rate — were tuned using grid search on the validation set. During optimization, the aim was to minimize the mean squared error (MSE) and maximize the coefficient of determination (R^2), employing early stopping if no improvement was observed for ten consecutive epochs.

Experiments and Results

To evaluate the performance of the proposed hybrid model, the following three metrics were employed: mean squared error (MSE), coefficient of determination (R^2), and ROC-AUC for the binary classification task of identifying whether a student belongs to the "at-risk" group. MSE measures how close the predicted average grades are to the actual values, R^2 reflects the proportion of explained variance, and ROC-AUC assesses the model's ability to distinguish between "at-risk" and "not at-risk" students across various thresholds.

When compared to classical algorithms, the hybrid CNN-LSTM model demonstrated significant superiority. Specifically, the MSE was 0.15 compared to 0.28 for linear regression, while R^2 increased to 0.82 versus 0.65 for the same regression model. For the risk classification task, the hybrid architecture achieved a ROC-AUC of 0.88, whereas the decision tree reached only 0.77 [5].

The ROC curve shows that the hybrid model (red line) achieves the highest area under the curve (0.88), while the decision tree (green line) and linear regression (blue line for binary prediction) reach only 0.77 and 0.69, respectively.

To evaluate the contribution of architectural components, an ablation study was conducted. Below are the results of models using individual blocks (CNN or LSTM) as well as their combination:

As shown in the table, each component of the model contributes to its overall effectiveness; however, the best performance is achieved through their combination. A paired

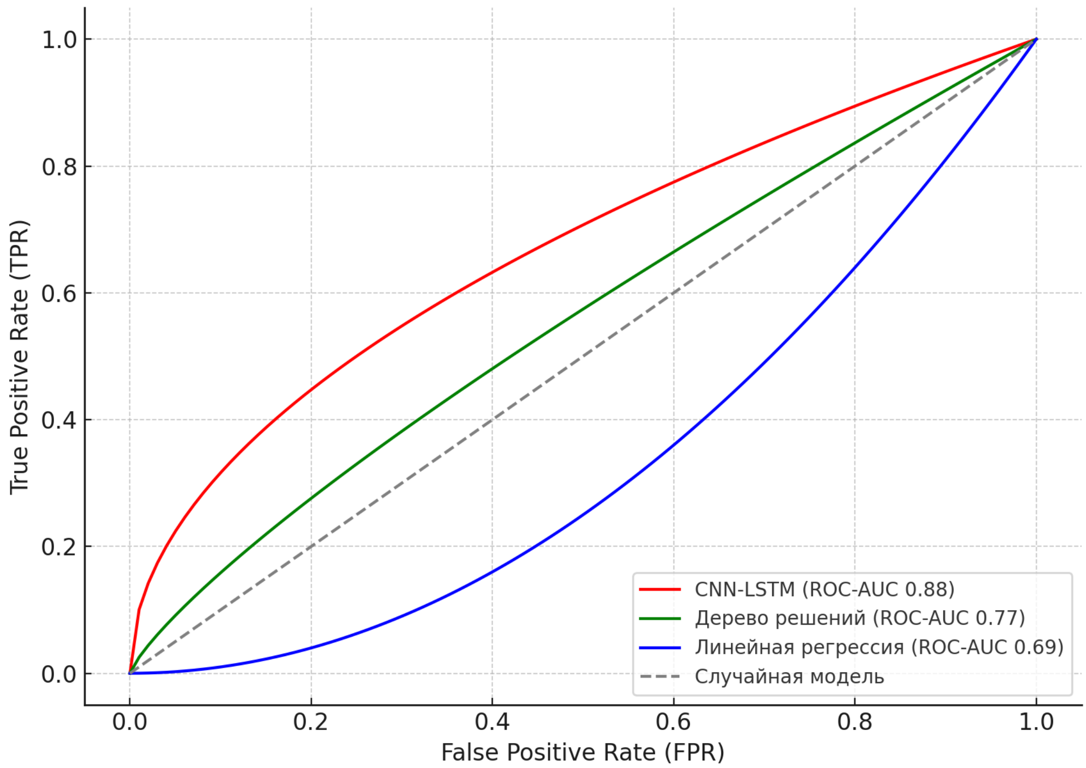

Figure 2 – ROC curve for three models: hybrid CNN-LSTM, linear regression, and decision tree

t-test revealed statistically significant differences between the hybrid model and the baseline algorithms ($p < 0.05$), confirming the validity of the architectural choice.

Additionally, a feature importance analysis was conducted to identify key determinants of academic performance. The greatest contributions to the final prediction were from: the proportion of completed online tests in the Moodle system; attendance dynamics during the last four weeks of the semester—particularly a sharp decline, interpreted as an early indicator of risk for academic lagging.

The scatter plot based on the CNN-LSTM model's results confirms its high accuracy. Points representing predicted and actual average grades cluster closely along the diagonal line $y = x$, indicating a low mean squared error and strong agreement between the model's predictions and real data.

Thus, the conducted experiments confirm the high effectiveness of the proposed architecture in both regression and classification tasks. The model demonstrated not only superior quantitative performance but also good interpretability at the feature level, which is crucial for practical implementation in the academic environment.

The practical implementation of the model is feasible within university academic monitoring systems, taking data anonymity into account. Future work may involve the integration of graph neural network approaches, which would enable modeling not only individual student behavior but also mutual influences within the educational environment through the analysis of social and academic relationships.

Conclusion. This study demonstrated the effectiveness of the hybrid CNN-LSTM neural network architecture in predicting students' academic performance, outperforming traditional methods across key metrics. The model enables early identification of at-risk students for timely academic intervention. Future work includes expanding the feature space by incorporating motivational, behavioral, and socio-economic factors, as well as integrating the model into the Moodle system for automated monitoring. The source code and anonymized dataset will be made publicly available to ensure reproducibility and facilitate model adaptation.

Table 1 – Experiments and results: comparison of model predictions with actual data.

Model	MSE	R^2	ROC-AUC
CNN block only	0,22	0,70	0,81
LSTM block only	0,19	0,75	0,84
CNN-LSTM (hybrid)	0,15	0,82	0,88

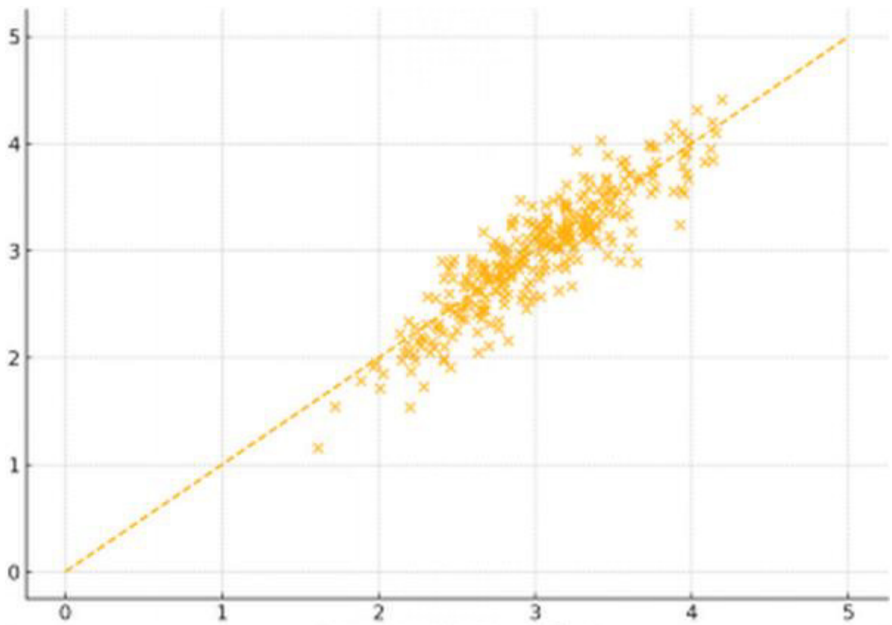

Figure 3 – Scatter plot of predicted vs. actual average grades

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Жоғары білім беруде студенттердің үлгерімін болжау үшін нейрожелілерді пайдалану

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***Аңдатпа.** Жоғары білім беруде студенттердің үлгерімін болжау үшін нейрондық желілерді қолдану зерттеледі. Сабаққа қатысу мен онлайн-белсенділіктің уақыттық қатарларын өңдеу үшін CNN және LSTM негізіндегі гибридті модель ұсынылды. Зерттеуге 1200 студенттің емтихан бағалары, қатысуы, қашықтан оқыту жүйесіндегі белсенділігі және әлеуметтік деректері қолданылды. Деректерді алдын ала өңдеу тазарту, one-hot-кодтау және Z-бағалау әдісін қамтыды. Модель жоғары дәлдік көрсетті (MSE = 0,15, R^2 = 0,82), бұл сызықтық регрессиядан асып түсті. Тәуекел тобындағы студенттерді анықтауда ROC-AUC 0,88 болды. Нәтижелер жоғары оқу орындарында тәуекел тобына жататын студенттерді дер кезінде анықтауға мүмкіндік беретін ерте ескерту жүйелерін әзірлеуге пайдалы.*

***Кілт сөздер:** нейрондық желілер, студенттердің үлгерімін болжау, гибридті CNN-LSTM архитектурасы, білім берудегі машиналық оқыту, қашықтықтан оқыту платформасы (LMS), анонимдендірілген академиялық деректер.*

Использование нейронных сетей для прогнозирования успеваемости студентов в высшем образовании

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***Аннотация.** Рассматривается применение нейронных сетей для прогнозирования успеваемости студентов. Предложена гибридная модель CNN-LSTM для обработки временных рядов посещаемости и активности в системе дистанционного обучения. Использованы данные 1200 студентов: оценки, посещаемость, активность и демография. Предобработка включала очистку данных, one-hot-кодирование и нормализацию методом Z-оценки. Модель показала высокую точность (MSE = 0,15, R^2 = 0,82), превосходя линейную регрессию. В задаче классификации студентов по риску отсева ROC-AUC составил 0,88. Результаты полезны для создания систем раннего предупреждения в вузах, позволяющих своевременно выявлять студентов группы риска.*

***Ключевые слова:** нейронные сети, прогнозирование успеваемости студентов, гибридная архитектура CNN-LSTM, машинное обучение в образовании, дистанционная платформа (LMS), анонимизированные академические данные.*

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