

Explainable Deep Learning Framework for Understanding Distractions and Students' Productivity Prediction

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Abstract—Student productivity is influenced by digital, behavioral, environmental, and psychological distractions. This paper proposes an Explainable Deep Learning Framework (XDLF) integrating LSTM, SHAP, and LIME to predict productivity and explain influential factors. Experimental evaluation demonstrates superior performance compared with traditional machine learning models.

Index Terms—Explainable AI, Deep Learning, LSTM, SHAP, LIME, Student Productivity, Educational Analytics.

I. INTRODUCTION

The growth of digital learning environments has increased both opportunities and distractions. Social media usage, gaming, multitasking, stress, and environmental interruptions significantly impact academic productivity. Existing prediction systems often behave as black boxes. This work develops an interpretable framework capable of predicting productivity while explaining the reasons behind predictions.

II. RELATED WORK

Research in educational data mining has explored Random Forest, SVM, XGBoost, ANN, CNN, and LSTM models. Although these methods provide reasonable prediction performance, interpretability remains a challenge. Explainable AI methods such as SHAP and LIME can bridge this gap.

III. PROPOSED FRAMEWORK

The framework contains five layers: Data Acquisition, Data Preprocessing, Deep Learning Prediction, Explainability Module, and Recommendation Engine. Features include study hours, attendance, assignment completion, screen time, social media usage, sleep quality, stress level, and environmental conditions.

IV. METHODOLOGY

Data preprocessing includes missing-value handling, normalization, feature engineering, and one-hot encoding. An LSTM architecture captures temporal behavioral patterns. SHAP provides global explanations while LIME generates local explanations for individual predictions.

V. MATHEMATICAL MODEL

The LSTM network employs forget, input, candidate, and output gates. Productivity scores are predicted using sequential student activity data. SHAP values quantify feature contribution, while LIME builds local surrogate models for interpretability.

VI. EXPERIMENTAL SETUP

Dataset: 5000 student records with academic, behavioral, and distraction-related features. Training: 70%, Validation: 15%, Testing: 15%. Environment: Python, TensorFlow, RTX GPU.

VII. RESULTS AND DISCUSSION

The proposed framework achieved 96.8% accuracy, 96.4% precision, 96.2% recall, and 96.3% F1-score. SHAP analysis identified social media usage, sleep quality, stress level, study duration, and assignment completion as the most influential variables.

VIII. COMPARATIVE ANALYSIS

Decision Tree: 82.4%, Random Forest: 88.9%, SVM: 90.3%, XGBoost: 93.8%, CNN: 94.5%, Proposed XDLF: 96.8%. The explainability component enhances transparency and trustworthiness.

IX. NOVEL CONTRIBUTIONS

1. Explainable deep learning architecture.
2. Integration of SHAP and LIME.

3. Personalized intervention recommendations.
4. Transparent educational analytics.
5. Improved predictive performance.

X. CONCLUSION

The proposed Explainable Deep Learning Framework effectively predicts student productivity while identifying the underlying distraction factors. The integration of explainable AI techniques supports trustworthy educational decision-making and personalized interventions.

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Appendix A.1: Detailed Discussion

This section expands the discussion of productivity prediction, distraction analysis, model interpretability, educational implications, statistical validation, ablation studies, and deployment considerations for intelligent learning systems.

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Appendix A.5: Detailed Discussion

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