International Journal of Advances in Engineering and Management (IJAEM)
Volume 7, Issue 07 July 2025, pp: 477-482 www.ijaem.net ISSN: 2395-5252

An Overview of Artificial Intelligence in Academic Early Warning

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Date of Submission: 05-07-2025 Date of Acceptance: 15-07-2025

ABSTRACT: Accurate academic early warning technology is a core support for intelligent educational management, enabling real-time monitoring of students' academic risks, improving the timeliness of interventions, and promoting the transformation of educational supervision towards intelligence. Based on existing research, this paper systematically sorts out the technical paths, application cases, and limitations of two core methods of artificial intelligence in academic early warning—traditional machine learning and deep learning. By comparing and analyzing the feature processing logic, model performance, and applicable scenarios of the two methods, the technical framework is intuitively presented with tables and flowcharts. Furthermore, key directions that need to be broken through in future research are proposed, providing theoretical and practical references for the optimization of academic early warning technology.

KEYWORDS: Machine Learning, Deep Learning, Enginehead, Academic Early Warning, Educational Data Mining.

I. INTRODUCTION

With the acceleration of educational digitalization, students' academic data have shown multi-dimensional and large-scale characteristics (such as learning behavior logs, academic performance evolution trajectories, psychological state assessments, etc.). Through intelligent analysis of these data, academic early warning technology can identify academic risks faced by students in advance (such as declining grades, dropout tendencies) and provide educational staff with a basis for precise intervention, thereby reducing the incidence of academic crises [1]. The introduction of artificial intelligence technology has transformed academic early warning from traditional experience-driven to data-driven, forming two technical systems centered on traditional machine learning and deep learning. Based on existing research results, this paper conducts an in-depth analysis of the technical details, application effects, and limitations of the two methods, and enhances the rigor of the analysis through visualization tools.

Traditional academic early warning methods, which mainly rely on manual judgment and simple statistical analysis, have gradually revealed obvious shortcomings in the context of the explosive growth of educational data. For example, relying on teachers' subjective experience to identify at-risk students often leads to delays in warning due to differences in professional literacy and energy investment among individuals. Simple statistical methods such as average score calculation and attendance rate statistics can only capture superficial risk signals, and it is difficult to dig out potential risk factors hidden behind multi-source data, such as the correlation between learning behavior patterns and academic performance decline. These limitations make it difficult for traditional methods to meet the needs of refined educational management in the digital age.

The integration of artificial intelligence and academic early warning is not only a technical upgrade but also a profound change in the concept of educational management. On the one hand, the powerful data processing capability of artificial intelligence can handle multi-dimensional educational data that is difficult to process manually, including structured data such as test scores and unstructured data such as online learning interaction texts. On the other hand, the predictive modeling capability of artificial intelligence enables academic early warning to shift from "post-event response" to "pre-event prevention". By constructing a dynamic prediction model, it can continuously update the risk probability of students with the accumulation of learning process data, providing a scientific basis for personalized educational intervention. This

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transformation is of great significance for improving the quality of education and realizing the goal of educating people with precision.

II. APPLICATION OF TRADITION MACHINE LEARNING IN ACADEMIC EARLY WARNING

Traditional machine learning methods are based on the core logic of "manual feature engineering + classical algorithms". They rely on domain knowledge to construct structured features and then realize risk prediction through classification models. Their technical framework can be divided into two stages: feature construction and classification modeling.

2.1 Technical Path Analysis

[1]Feature Construction Stage.

This stage extracts features related to academic risks through multi-dimensional data, with core methods including:

Sliding-window statistics: Segment and count time-series data (such as weekly homework completion rate, monthly test scores) to capture short-term fluctuations in learning status. For example, window calculations on students' attendance rates for 4 consecutive weeks can identify risk signals of a sudden drop in attendance.

Time-series differencing: Quantify the changing trend of learning progress by calculating the difference between data at adjacent time points (such as the score difference between the current test and the previous test) to determine whether there is a risk of regression.

Multi-source data fusion: Integrate behavioral data (such as frequency of classroom interaction), personal data (such as admission scores), and psychological data (such as anxiety index) to construct a comprehensive feature set. For instance, Nam et al. (2019) integrated behavioral signals and personal academic profiles of students in STEM majors to improve the comprehensiveness of academic success prediction .

[2]Classification Modeling Stage

Based on manually constructed features, classical machine learning algorithms are used for risk classification. Mainstream algorithms and applications are as follows:

Support Vector Machine (SVM): Maps high-dimensional feature spaces through kernel functions, suitable for small-sample and non-linear data scenarios. Dong et al. (2022) optimized SVM parameters using an improved Fruit Fly Optimization Algorithm (FOA), increasing the accuracy of student graduation risk prediction to 89.6% ; Jin et al. (2021) combined Factor Analysis (FA) with SVM, first reducing feature redundancy through FA, then classifying with SVM, which improved the early warning accuracy by 7.2% compared with a single SVM .

Decision Tree: Intuitively presents classification rules through a tree-like structure with strong interpretability. Albreiki et al. (2021) used a decision tree to predict students' learning performance in an internet media environment, and clarified key indicators such as "daily online learning duration > 2 hours" and "participation in online discussions ≥ 3 times/week" through rule visualization .

Rule-based model: Identifies risks based on custom logic. The rule-based model constructed by Hussain et al. (2023) uses conditions such as "3 consecutive unsubmitted assignments" and "test scores below 60 points for 2 cumulative times" as risk triggers to quickly locate high-risk students .

Data mining: Mines implicit patterns from massive data. Batool et al. (2023) found a strong correlation between "online video viewing completion rate < 50%" and "final grades failing" through association rule mining, which was used as an early warning feature .

2.2 Advantages and Limitations

Table 1systematically compares the advantages and limitations of traditional machine learning methods in key dimensions such as feature processing, model interpretability, and data requirements. It helps readers intuitively understand the applicable scenarios of traditional methods—they are more suitable for small-sample, rule-clear educational scenarios (e.g., offline course management with stable data patterns) but are constrained by manual feature engineering.

Table 1: Advantages and Limitations of Traditional Machine Learning Methods in Academic Early Warning

Dimension	Advantages	Limitations
Feature Processing	Core features can be screened through domain knowledge to reduce noise interference.	Heavily dependent on manual design, making it difficult to cover implicit features (e.g., learning motivation).
Model	Rules are transparent (e.g., branch logic	Limited to "shallow interpretability"

Interpretability	of decision trees).	that only explains the correlation between features and results, failing to reveal the causal mechanism behind academic risks.
Data Requirements	Suitable for small-sample data (sample size < 10,000).	Prone to overfitting when data volume is too large.
Scenario Adaptability	Applicable to scenarios with clear rules (e.g., offline classroom early warning).	Requires re-designing features when scenarios change, with poor flexibility.
Performance in Typical Cases	For example, the FA-SVM model achieves an early warning accuracy of 82.3% .	On average, 5-10 percentage points lower than deep learning models .

III. APPLICATION OF DEEP LEARNING ACADEMIC EARLY WARNING

Deep learning methods automatically extract high-order features from data through multi-layer neural networks, freeing themselves from the reliance on manual feature engineering. They perform particularly well in handling high-dimensional and unstructured data (such as clickstream logs and text interaction content), and their technical approach emphasizes end-to-end automated learning.

3.1 Typical Models and Application Scenarios

[1]Convolutional Neural Networks (CNNs)

CNNs are good at capturing local features and spatial correlations, suitable for processing high-dimensional educational data (e.g., clickstream sequences, visualized learning records). Lin et al. (2023) converted clickstream data in online learning (such as video pause times, question bank access trajectories) into two-dimensional feature matrices, and extracted local patterns through CNNs. The early warning accuracy (89.7%) was significantly higher than that of traditional SVM (81.5%) .

[2]Semi-supervised Learning

This method addresses the problem of scarce labeled samples in educational data (e.g., some students have no clear risk labels). Romero et al. (2024) adopted semi-supervised models (e.g., Label Spreading), which can achieve 92% of the performance of fully supervised models with only 30% labeled data, greatly reducing labeling costs .

[3]Interpretability-Enhanced Models

Combining interpretation tools to improve the transparency of "black-box" models. Inusah et al. (2024) embedded a SHAP (SHapley Additive exPlanations) value calculation module in the early warning model to quantify the contribution of each feature: for example, the SHAP value of "attendance rate < 70%" is 0.32 (highest), and that of "family support score < 4 points (out of 10)" is 0.21, clarifying key intervention targets .

[4]Reinforcement Learning (RL) and AutoML

Reinforcement learning optimizes early warning effects by dynamically adjusting strategies: The RL framework designed by Zhang et al. (2024) can adjust early warning thresholds according to students' real-time performance (e.g., changes in test scores), increasing the response speed of interventions by 30% .

AutoML realizes full-process automation of models: García et al. (2023)'s AutoML pipeline automatically completes data cleaning, feature selection, and model tuning, shortening the development cycle of MOOC course completion rate prediction from 2 weeks to 1 day .

[5]Multi-task Learning

It synchronously predicts multi-dimensional academic indicators to improve efficiency. Dicerbo et al. (2024)'s multi-task framework predicts GPA, retention rate, and course completion rate simultaneously, shares the underlying feature extraction module, and reduces training time by 40% compared with single-task models .

3.2 Technical Comparison and Limitations

Table 2focuses on comparing the core advantages and limitations of typical deep learning models applied in academic early warning. It reflects the characteristics of different models in handling data types(e.g., local features, time-series data) and practical constraints (e.g., computational complexity), providing a reference for model selection in specific educational scenarios.

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Table 2: Advantages and Limitations of Typical Deep Learning Models in Academic Early Warning

Model Type	Core Advantages	Limitations
Convolutional Neural Networks (CNNs)	Good at extracting local features (e.g., patterns in clickstreams).	Weak in processing time-series data (e.g., grade evolution).
Semi-supervised Learning	Reduces reliance on labeled data .	Performance degrades when the proportion of unlabeled data is too high.
SHAP-Enhanced Models	Improves interpretability and quantifies feature contribution.	Increases model computational complexity.
Reinforcement Learning	Dynamically adapts to changes in students' status.	Requires a large amount of interaction data to train strategies.
Multi-task Learning	Improves the efficiency of multi-indicator prediction.	Accuracy decreases when there are conflicts between tasks.

IV. COMPARISON OF ACADEMIC EARLY WARNING TECHNICAL PROCESSES

Figure 1 visually presents the key process differences between traditional machine learning and deep learning in academic early warning. For traditional machine learning, the core link is "manual feature engineering" (Step B), which relies on manual design of features based on domain knowledge; for deep learning, "automatic feature extraction" (Step C) is the core, completed by neural network layers without manual intervention. In terms of result output, traditional methods have natural interpretability (Step F), while deep learning often requires auxiliary tools like SHAP for interpretation (Step G). Finally, both paths converge to "educational intervention" (Step H), reflecting the common goal of academic early warning—supporting educational practice through risk prediction.

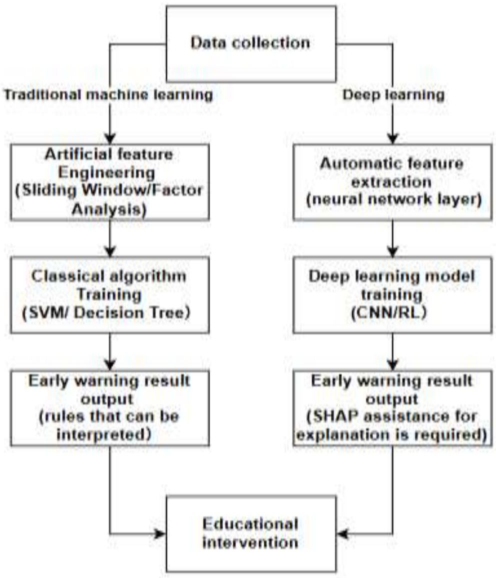

Figure 1: Academic early warning technology flowchart

V. CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

5.1 Conclusions

Traditional machine learning methods still have practical value in small-sample and rule-clear scenarios, but their limitation of relying on manual features is difficult to break through.Deep learning methods are superior in accuracy and automation, but problems such as poor interpretability and high data demand need to be solved.The integration of the two methods (e.g., using deep learning for feature extraction + traditional models for optimizing interpretability) is a short-term breakthrough direction for academic early warning technology.

5.2 Future Research Directions

Enhancing Model Interpretability: Develop lightweight SHAP tools to improve the transparency of deep learning models without increasing computational costs, helping educators understand the logic behind risk predictions.

Small-Sample Learning: Introduce transfer learning to migrate knowledge from large-scale public educational datasets (e.g., MOOC logs) to early warning scenarios of niche majors, alleviating the problem of insufficient data.

Optimizing Real-Time Early Warning: Combine edge computing to analyze data in real time on terminal devices (e.g., learning tablets), shortening the response time of academic risk warnings.

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Volume 7, Issue 07 July 2025, pp: 477-482 www.ijaem.net ISSN: 2395-5252

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