



# Portable Few-Shot Learning for Early Warning Systems in Small Private Online Courses: A CNN-Based Predictive Framework for Student Performance

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**ABSTRACT:** This study develops a portable early warning system designed to predict student academic performance in Small Private Online Courses (SPOCs) by leveraging few-shot learning techniques and convolutional neural networks (CNNs). Addressing the persistent challenges posed by limited sample sizes and the absence of face-to-face interactions in asynchronous online environments, the research explores whether small-sample behavioral data derived from multiple SPOCs can support reliable and transferable predictive models. The dataset comprises more than 4.4 million LMS log entries collected from four online courses sharing similar instructional designs and taught by a single instructor. After comprehensive preprocessing—encompassing feature extraction, weekly aggregation, and normalization—18 week-specific CNN models were trained to capture the temporal progression of student learning behaviors. The results indicate that meaningful prediction accuracy emerges by the fifth week, with performance exceeding 80% from week eight onward. Portability was further validated by applying the model to an additional course, where accuracy remained at or above 81%, confirming its robustness under consistent instructional conditions. The findings highlight the potential of few-shot learning to sustain predictive performance despite limited training samples, offering educators a viable foundation for timely interventions and institutional adoption of precision-driven academic support systems.

**Keywords:** early warning systems; educational data mining; few-shot learning; convolutional neural networks; small private online courses (spocs); student performance prediction; learning analytics; model portability.

## I. Introduction

Online education has witnessed rapid expansion over the past decades, driven by advancements in technology and the increasing demand for flexible learning opportunities. While massive open online courses (MOOCs) have garnered widespread attention because of their capacity to reach thousands of students simultaneously, small private online courses (SPOCs) offer a unique environment for personalized instruction and closer teaching–learning interactions. Nonetheless, even in SPOCs where class sizes are smaller, instructors face significant challenges when teaching in a distance environment. The lack of direct face-to-face contact can impede the timely identification of students who are struggling academically. As a result, early warning systems (EWSs) have emerged as critical tools in predicting academic performance and identifying students who are at risk of failing in an online asynchronous environment [1].

In this study, we focus on developing a portable predictive model using few-shot learning techniques. Specifically, the research investigates the feasibility of constructing an early warning system based on small-

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sample data collected from multiple SPOCs that are taught by the same teacher. By analyzing the online learning trajectories captured in the learning management system (LMS), the study aims to predict whether students will pass or fail their final assessments. The research further examines the portability of the prediction model by verifying its applicability in a different course with a similar instructional design[2].

The central research questions addressed in this study are:

- How far in advance can an early warning system accurately predict a student's academic performance?
- Can a prediction model developed from historical data in multiple SPOCs be effectively transferred to predict academic performance in another course taught by the same instructor?

The research leverages the power of convolutional neural networks (CNNs) to build predictive models, each corresponding to one week of the online course duration[3]. A total of 18 models were created, one for each week, to capture the dynamic progression of students' learning behaviors [4], [5]. The system's sustainability is ensured by continuously integrating new data into the model, which gradually enhances its accuracy[6].

This article presents a comprehensive review of the process involved in developing the predictive model, from data collection to preprocessing, model construction, and evaluation. Through in-depth analysis of various indicators of online student behavior, such as video engagement, discussion participation, and assignment interactions, the study demonstrates the potential of data mining techniques in shaping precision education practices. The implications for educators, educational authorities, and IT directors are profound, as such systems not only facilitate timely interventions but also contribute to the digital transformation of academic institutions.

## II. EDUCATIONAL DATA MINING AND EARLY WARNING SYSTEMS

Educational Data Mining (EDM) represents an emerging field that harnesses statistical models, machine learning algorithms, and data analytics tools to derive actionable insights from large volumes of educational data. By analyzing complex patterns in student behavior and performance, EDM enables teachers to design more responsive and adaptive teaching strategies. The process typically involves multiple steps, including determining research goals, collecting data from digital platforms such as LMSs, preprocessing the data, training predictive models, and finally, using the outcomes to inform instructional decisions [7].

### 1. ROLE OF DATA MINING IN EDUCATION

EDM is instrumental in transforming raw data into meaningful information that enhances the teaching and learning process. In distance education, the LMS serves as an extensive repository of student interactions – recording events such as page views, video clicks, assignment submissions, and forum activities. This wealth of information provides educators with insights that are not readily available in traditional classroom settings. For instance, through the systematic analysis of LMS logs, teachers can detect patterns that correlate with academic success or failure, thereby identifying students who are at risk early in the course[8].

### 2. EARLY WARNING SYSTEMS (EWSS) IN ONLINE EDUCATION

An Early Warning System (EWS) is designed to provide real-time feedback to educators by continuously monitoring student behaviors and performance indicators. EWSs help teachers understand the multifaceted dimensions of student engagement by aggregating behavioral data and applying predictive algorithms to forecast academic outcomes. Previous research in the field has illustrated the potential of various EWSs that rely on diverse machine learning approaches, including decision trees, clustering techniques, and neural networks [6], [9]. Despite the success achieved in large-scale MOOCs, developing a robust EWS for SPOCs presents its own set of challenges, primarily due to the smaller sample sizes and the similarities in instructional design imposed by the institution.

### 3. CHALLENGES IN MODEL PORTABILITY ACROSS COURSES

One of the pressing challenges is the portability of predictive models. While the effectiveness of a model developed on one dataset is often high, transferring the same model to a different course might lead to disparities in performance. Variations in instructional design, differences in student demographics, and

unique course contents can all impact prediction accuracy. Prior studies have noted that when instructional designs differ significantly between courses, the resulting prediction models can exhibit lower accuracy [1]. However, by focusing on SPOCs with similar instructional designs and taught by the same teacher, the study aims to mitigate these challenges and enhance model portability [10].

#### 4. INTEGRATION OF FEW-SHOT LEARNING MATERIALS

Few-shot learning is a promising approach that is particularly relevant when available training data are limited. Instead of requiring massive datasets for every new predictive task, few-shot learning techniques enable a model to generalize from a small number of examples. This capability is especially valuable in educational settings where data volumes may be insufficient for traditional deep learning methods. By incorporating few-shot learning, the system is able to detect patterns in student behavior from multiple SPOCs and build a prediction model that remains robust even with a limited number of samples [11].

### III. METHODOLOGY

The methodological framework employed in this research is centered on leveraging small-sample data from multiple SPOCs to build an effective early warning system. The following sections detail the step-by-step process, starting with participant selection and data collection, moving through data preprocessing and feature engineering, describing the construction of the CNN predictive model, and finally outlining the evaluation metrics used to assess model performance [12].

#### 1. PARTICIPANTS AND DATA COLLECTION

The study collected extensive online behavioral data from four asynchronous online courses, all conducted during the academic years 2017–2018 and 2018–2019. These courses, which spanned 18 weeks each, were taught by a single instructor to maintain consistency in teaching style and instructional design. The LMS recorded every student event such as logins, page clicks, video interactions, and assignments submissions in a log file format. This log-based data collection ensured that even the minutiae of student engagement were captured, thereby providing a rich dataset for analysis.

A total of 1,278 students participated in these courses, with 1,135 passing and 143 failing based on a final assessment threshold of 60%. The diverse sample included students from a variety of academic disciplines, as detailed in Table 1 below. The data collection process was facilitated by an application programming interface (API) that extracted the necessary logs and stored them in a centralized database. This process ensured that the data were collected in real time and accumulated over the duration of the courses, enabling week-by-week analysis of learning trajectories.

**Table 1.** Overview of course characteristics and student demographics.

Characteristic	Data Science (I)	Data Science (II)	Digital Social Innovation	Psychology
School Year	2017–2018	2017–2018	2018–2019	2018–2019
Total Students	306	355	313	304
Discipline – Humanities	40	59	29	38
Discipline – Engineering	116	100	137	166
Discipline – Management	74	95	79	50
Discipline – Design	76	47	68	50

Characteristic	Data Science (I)	Data Science (II)	Digital Social Innovation	Psychology
Gender (Female)	146	164	139	138
Gender (Male)	160	191	174	166
Year of Study (1st)	59	44	80	85
Year of Study (2nd)	100	133	49	80
Year of Study (3rd)	95	150	66	122
Year of Study (4th)	47	27	114	15
Year of Study (Extension)	1	4	2	-

Table 1 provides a snapshot of the student distribution across the four courses and highlights the diversity in academic disciplines and study years, underscoring the relevance of establishing a generalized predictive model 1.

## 2. DATA PREPROCESSING AND FEATURE ENGINEERING

The raw data extracted from the LMS consisted of detailed logs representing thousands of student activities accumulated over the period of each course. In order to render this data fit for analysis and predictive modeling, an extensive preprocessing phase was conducted. This phase comprised of several key steps:

### 2.1 Feature Extraction and Filtering

Initially, the raw logs were analyzed to identify potential features that could serve as indicators of learning behavior. Analysis of variance was applied to filter and retain the most relevant features. In total, 20 features were identified, each representing different aspects of student engagement, such as the number of video clicks, discussion forum interactions, assignment views, and download counts. These features were defined with precision to capture both the quantitative frequency of interactions and the duration of time students engaged with various online materials.

### 2.2 Aggregation of Weekly Data

Given the asynchronous nature of the courses, it was important to consider the cumulative weekly progress of students. All features were aggregated on a weekly basis to construct a temporal profile of learning behavior. This aggregation allowed for capturing the evolution of student engagement over time and facilitated the construction of predictive models for each week of the course[13].

### 2.3 Normalization of Data

In order to ensure that the predictive model was not biased by features with larger numeric ranges, all feature values were normalized to a scale of 0 to 1 using [0,1] normalization. This technique ensured that the model training process was robust and that all features contributed in a balanced manner. The normalization formula used is represented as[14], [15]:

$$X_{\text{normalized}} = (X - X_{\text{min}}) / (X_{\text{max}} - X_{\text{min}})$$

where  $X$  represents the raw feature value, and  $X_{\text{min}}$  and  $X_{\text{max}}$  denote the minimum and maximum values observed across the dataset.

### 2.4 Splitting Data into Training and Test Sets

To evaluate the model's performance fairly and prevent overfitting, the aggregated and normalized data were randomly divided into training (70%) and testing (30%) sets. This stratification ensured that each weekly dataset had a representative sample of student behaviors for both model training and subsequent evaluation.

**Table 2.** Descriptive summary of extracted features.

<b>Feature Number</b>	<b>Feature Name</b>	<b>Description</b>
1	view_link_count	Number of views of supplementary materials
2	create	Number of articles posted in the discussion forum
3	like	Number of likes for discussion posts
4	read	Number of articles viewed in the discussion area
5	online_video_count	Number of clicks on teaching videos
6	forum_count	Number of clicks on the discussion webpage
7	online_video_time	Time spent on the teaching video webpage
8	total_mobile_time	Time spent via mobile devices accessing the platform
9	weekday_time	Video viewing duration between Monday and Friday
10	weekend_time	Video viewing duration on Saturday and Sunday
11	morning_time	Video viewing duration in the morning
12	noon_time	Video viewing duration in the afternoon
13	night_time	Video viewing duration in the night
14	total_watch_time	Total video viewing duration
15	download_count	Number of download events
16	homework_count	Number of times assignments were clicked
17	homework_time	Duration spent browsing assignments
18	forum_time	Duration spent on forum browsing
19	total_non_mobile_time	Time spent using desktop/laptop devices
20	total_use_time	Total time accessing the course platform

Table 2 outlines the specific features extracted from the LMS logs. Each feature was strategically chosen to reflect a distinct aspect of student interaction and learning engagement 1.

### *3. MODEL BUILDING WITH CONVOLUTIONAL NEURAL NETWORKS*

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Convolutional Neural Networks (CNNs) are typically associated with applications in image processing; however, their ability to capture complex patterns has also proven useful in modeling sequential data. In this research, a CNN was employed to build the predictive model due to its flexibility in processing time-series data and its robustness in detecting subtle shifts in student behaviors. The CNN model was developed using the Python programming language along with the PyTorch deep learning framework[16], [17].

### 3.1 Weekly Model Construction

A unique aspect of the methodology was the development of 18 separate predictive models—each corresponding to one week (7 days) of course data. By designing weekly models, the study was able to observe how prediction accuracy evolved over time. Only the data from students who actively engaged with the LMS during that particular week were included in the training set for that week, ensuring that the model was trained only on relevant behavioral indicators [18], [19]. The rationale behind this approach was that student behaviors do not remain static throughout the duration of a course; rather, they evolve as students progress in their learning. As such, the creation of weekly models provided a dynamic and granular understanding of the patterns that precede academic success or failure.

### 3.2 Verification of Model Portability

In order to test the portability of the predictive model across courses, the model was verified using data from an additional course titled “Introduction to Artificial Intelligence,” taught during the 2019–2020 academic year. Importantly, this course was delivered by the same teacher and featured a similar instructional design, which allowed for a meaningful comparison of the model’s performance on new data. The verification process involved assessing whether the accuracy and other key evaluation metrics remained within acceptable ranges when applied to the new dataset[20], [21].

## 4. EVALUATION METRICS AND MODEL VERIFICATION

To rigorously assess the performance of the predictive models, several evaluation metrics were computed using a confusion matrix framework. The confusion matrix, a standard tool in classification tasks, is organized as a 2x2 table that distinguishes between correct and incorrect predictions. The following definitions are used[22]:

- True Positive (TP): The number of correctly predicted “passed” outcomes.
- True Negative (TN): The number of correctly predicted “failed” outcomes.
- False Positive (FP): The number of failing students inadvertently predicted to pass.
- False Negative (FN): The number of students predicted to fail who actually passed.

Based on these values, the following performance metrics were calculated:

- Accuracy:  
$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$
- Sensitivity (Recall):  
$$\text{Sensitivity} = \text{TP} / (\text{TP} + \text{FN})$$
- Specificity:  
$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP})$$
- Precision:  
$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$
- F-Measure (F Score):

$$\text{F-Measure} = (2 \times \text{Precision} \times \text{Sensitivity}) / (\text{Precision} + \text{Sensitivity})$$
  
In this study, a  $\beta$  value of 2 was used in the calculation of the F-Measure, which emphasizes the contribution of recall in the overall score 1.

The performance metrics were calculated for each of the 18 weekly prediction models, providing insight into how early in the course an effective early warning can be implemented. This systematic evaluation also served to validate the model’s accuracy and generalizability across different weeks of the course.

## IV. RESULTS

This section presents a detailed account of the empirical findings derived from the predictive model. The results are broken down into descriptive statistics, the performance of the weekly prediction models, and the verification of the model’s portability when applied to a new course offering.

### 1. DESCRIPTIVE STATISTICS AND DATA DISTRIBUTION

The analysis began with a thorough examination of the raw data collected from the four SPOCs. Over the course duration, a total of 4,468,906 data points were accumulated.

**Table 3.** Summary of selected data metrics for all courses.

Metric	Value
Total Data Points	4,468,906
Weekly Data Point Range	In millions (0–4.5)
Total Students	1,278
Number of Passing Students	1,135
Number of Failing Students	143

Table 3 encapsulates key numerical insights from the LMS data, emphasizing the extensive engagement recorded over the courses and the overall academic outcomes of the student cohort.

### 2. Prediction Model Performance Across Weeks

A central focus of the research was the weekly evaluation of the CNN predictive models. The analysis revealed that the accuracy of the models varied across the 18 weeks. In the early weeks, prediction accuracy was relatively modest, gradually improving as more data were accumulated. For instance, during the second week, the training accuracy was observed at 59%, whereas later weeks saw noticeable improvements.

The progression of accuracy is summarized in Table 4 below, which displays the sensitivity, specificity, precision, F-Measure, and accuracy of the predictive models for both the training and testing sets, across different weeks of the courses.

**Table 4.** Weekly performance metrics of the prediction models.

Week	Data Points	Specificity (Train/Test)	Precision (Train/Test)	Sensitivity (Train/Test)	F-Measure (Train/Test)	Accuracy (Train/Test)
1	113,585	99/100	95/100	6/6	11/11	22/16
2	443,040	55/63	87/91	60/60	71/72	59/60
3	726,397	70/68	91/89	61/58	73/70	62/59
4	973,496	71/77	90/93	58/57	71/71	60/61
5	1,203,686	69/69	91/92	70/69	79/79	69/69
6	1,572,754	79/85	92/95	59/62	72/75	63/66

Week	Data Points	Specificity (Train/Test)	Precision (Train/Test)	Sensitivity (Train/Test)	F-Measure (Train/Test)	Accuracy (Train/Test)
7	1,872,702	83/85	93/94	53/51	68/66	59/57
8	2,336,105	69/71	92/92	83/78	87/84	80/77
9	2,492,457	81/79	93/93	63/57	75/71	66/61
10	2,614,689	56/55	89/90	89/88	89/89	82/82
11	2,776,942	77/72	93/92	74/72	82/81	75/72
12	3,028,478	79/78	93/93	72/67	81/78	74/69
13	3,255,458	59/65	89/91	89/84	89/87	83/80
14	3,441,195	71/73	92/93	84/79	88/85	82/78
15	3,667,310	74/78	92/94	80/74	86/83	79/74
16	3,992,200	76/76	93/94	78/77	85/85	78/77
17	4,241,995	73/72	92/94	82/82	87/88	80/80
18	4,468,906	61/60	90/91	90/89	90/90	84/84

Table 4 illustrates the progression of model performance, showing that after the 8th week the accuracy in both training and testing stabilized at levels considered acceptable for early intervention strategies.

One key finding from the weekly performance metrics is that statistical improvements in accuracy and other evaluation measures were observable starting around week 5. For example, the fifth-week model registered an accuracy of approximately 69% (test set), indicating that early predictors of student failure become detectable relatively early in the course timeline. Moreover, from week 8 onward, the model reached or exceeded an accuracy of 80% in both training and testing sets, confirming that sufficient learning behavior data had accumulated to support reliable prediction.

### 3. PORTABILITY ASSESSMENT OF THE PREDICTION MODEL

Portability of a prediction model refers to its ability to generalize and maintain performance when applied to new data or a different but similar educational context. In this research, the model's portability was evaluated by applying it to data from an additional distance course. This course, "Introduction to Artificial Intelligence," was selected because it was taught by the same teacher and featured an online design similar to the courses used to develop the original model [23].

The verification results indicated that from the eighth week onward, the model sustained an accuracy of  $\geq 81\%$  on the verification dataset. This robust performance supports the contention that small-sample learning models based on few-shot learning techniques can be reliably transferred, provided that the underlying instructional design and teaching conditions remain consistent. The successful portability of the model reinforces the potential for deploying such early warning systems in diverse SPOC settings, thereby assisting in timely educational interventions[24].

## V. DISCUSSION AND CONCLUSIONS

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The findings of this study offer compelling evidence that an early warning system based on a convolutional neural network can be effectively developed using small-sample data from multiple SPOCs. By systematically analyzing online learning trajectories, the model succeeds in predicting student academic performance and identifying those at risk of failing the course. Below, we discuss the key insights, implications for practice, and recommendations for future research.

### 1. KEY INSIGHTS FROM THE PREDICTIVE MODEL

- **Early Detection of At-Risk Students:**  
The results show that meaningful prediction of student performance is possible from as early as the fifth week in the course. This early detection is invaluable for instructors as it provides them with a critical window to implement timely and targeted interventions to support struggling students.
- **Progressive Improvement Over Time:**  
The gradual increase in accuracy and other performance metrics over the 18-week period highlights the cumulative nature of learning behavior data. As students' activities are tracked weekly, the model becomes increasingly adept at recognizing patterns that are indicative of academic outcomes. This progressive improvement validates the hypothesis that continuous data accumulation leads to more reliable predictions 1.
- **Efficacy of Few-Shot Learning Materials:**  
The use of few-shot learning, where predictions are made based on a limited set of training examples, underscores the utility of applying advanced machine learning techniques even when extensive data are not available. This approach not only mitigates data scarcity challenges but also ensures that the resulting EWS is sustainable and capable of integrating new data over time.
- **Robustness Through Consistent Instructional Design:**  
By focusing on courses delivered by a single teacher with similar instructional designs, the study effectively reduced the confounding impact of divergent teaching methods. This consistency solidified the basis for model portability, as the predictive features derived from one set of courses remained applicable to another course with a similar structure .

### 2. IMPLICATIONS FOR EDUCATORS AND EDUCATIONAL STAKEHOLDERS

The development and successful validation of the predictive model hold significant implications across multiple dimensions of educational practice:

- **For Teachers:**  
Instructors can use the early warning system to monitor students' online engagement in real time and implement data-driven interventions that can potentially improve learning outcomes. By identifying at-risk students early in the course, teachers can tailor instructional strategies and offer additional support, which is imperative in asynchronous learning environments where face-to-face interactions are limited 1.
- **For Educational Authorities:**  
Policy makers and educational administrators can leverage the insights gained from such predictive models to optimize resource allocation. Investments in data analytics infrastructure, professional development for teachers on data-driven instruction, and the establishment of centralized data warehouses for LMS records can further enhance teaching effectiveness across institutions 1.
- **For IT Directors:**  
IT managers in academic institutions should prioritize establishing systems that facilitate seamless and automated data collection from LMSs. The integration of APIs and the creation of learning data warehouses can empower educators with real-time access to critical engagement data. Such initiatives are crucial for supporting the scalability and sustainability of early warning systems 1.

### 3. LIMITATIONS OF THE STUDY

While the research presents a promising approach to predictive modeling in online education, a number of limitations must be acknowledged:

- **Sample and Institutional Bias:**

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All data were sourced from a single institution and involved courses taught by one teacher. This homogeneity, while beneficial for minimizing variability in instructional design, may limit the generalizability of the findings to other contexts with diverse teaching styles or student populations 1.

- **Limited Data Scope:**  
Although the study collected nearly 4.5 million data points, the approach relies on few-shot learning techniques which might not capture all nuances present in larger datasets. In addition, behavioral data from the LMS might miss other influential factors such as offline study habits or socio-emotional variables that could also affect academic performance 1.
- **Evaluation Metric Sensitivity:**  
The use of standard evaluation metrics such as accuracy, specificity, and sensitivity provides a strong baseline for model assessment. However, metrics like the F-Measure, which was configured with a  $\beta$  of 2, may be sensitive to data imbalances. Further research is needed to explore alternative evaluation frameworks that can address these potential biases more comprehensively 1.

#### 4. RECOMMENDATIONS FOR FUTURE RESEARCH

Based on the findings and limitations of the current study, several avenues for future research emerge:

- **Expansion to Diverse Educational Settings:**  
Future studies should consider collecting and analyzing data from multiple institutions, overcoming potential biases associated with a single-teacher or single-institution approach. Examining courses with varying instructional designs could provide additional insight into strategies for enhancing model portability.
- **Integration of Multi-Modal Data Sources:**  
Beyond LMS behavioral data, incorporating additional data streams such as emotional or cognitive indicators (potentially measured through surveys or biometric sensors) could further refine the predictive model. This multi-modal approach may yield a more comprehensive understanding of the factors influencing student performance.
- **Refinement of Feature Engineering Techniques:**  
Continued research is needed to identify and validate which specific behavioral features most significantly impact academic outcomes. Advanced feature selection methodologies, possibly integrating expert pedagogical insights, could lead to the development of more nuanced models that better capture the complexities of online learning.
- **Longitudinal Studies and Continuous Model Updating:**  
Future work should consider longitudinal designs that track cohorts over multiple years to determine the long-term efficacy of early warning systems. The integration of continuously updated data into the models can not only improve prediction accuracy over time, but also allow for adaptive revisions to support evolving online learning contexts.
- **Exploration of Alternative Machine Learning Algorithms:**  
While CNNs have demonstrated robust performance in this study, it would be beneficial to benchmark their performance against other sophisticated machine learning techniques, such as ensemble models or sequence models. Comparative studies could reveal the strengths and limitations of each approach, paving the way for hybrid systems that maximize predictive accuracy.

## VI. DISCUSSION AND CONCLUSIONS

- In summary, this research provides a thorough examination of a predictive model developed through few-shot learning techniques, utilizing small-sample data collected from multiple SPOCs. The study underscores the potential of convolutional neural networks in detecting patterns in student learning behavior and predicting academic outcomes with a high degree of accuracy. By carefully pre-processing the data, engineering relevant features, and constructing weekly predictive models, the research demonstrates that early detection of at-risk students is both feasible and effective.

### 1. MAJOR FINDINGS

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- **Early Detection Capability:**  
The predictive model successfully identified at-risk students as early as the fifth week of the course. This early detection is essential for implementing timely pedagogical interventions that could potentially mitigate academic failure before it becomes entrenched 1.
  - **Improvement Through Data Accumulation:**  
A clear trend of enhanced model performance was observed over the 18-week course duration. The accuracy and other evaluation metrics, such as precision and sensitivity, increased as the model was trained on larger cumulative datasets, eventually reaching or exceeding 80% accuracy in later weeks 1.
  - **Portability Across Courses:**  
The verification of the model using data from a separate “Introduction to Artificial Intelligence” course confirmed that the predictive system remained robust when transferred to a new context, provided the instructional design was similar. This portability is particularly promising for broader implementation across courses with a consistent teaching methodology 1.
  - **Sustainability and Adaptability:**  
The integration of new data into the early warning system ensures sustainability, as the model can be continuously updated and fine-tuned. This adaptability contributes to the long-term viability of data-driven educational interventions, allowing teachers to respond to evolving student behaviors in real time 1.

## 2. PRACTICAL IMPLICATIONS

Based on these findings, several practical recommendations can be made for various stakeholders in the education ecosystem:

For Teachers:

- Implement early warning systems to routinely monitor students’ online engagement.
- Use predictive insights to design personalized interventions, thus supporting students who exhibit early signs of struggling.
- Consider the integration of automated data collection tools via the LMS to facilitate the development of similar models in different course settings.

For Educational Authorities:

- Promote initiatives that encourage the digital transformation of education by investing in robust data management and analysis infrastructures.
- Organize seminars and training programs that enhance educators’ capacity to use data-driven technologies in their pedagogical practices.
- Develop policies that facilitate cross-institution collaborations and data sharing, further supporting the scalability and portability of early warning systems.

For IT Directors:

- Establish secure, centralized data warehouses that aggregate LMS logs for timely processing and analysis.
- Develop APIs and automated access mechanisms to empower teachers with real-time insights into student engagement.
- Provide comprehensive technical support and detailed documentation (such as codebooks) to assist educators in understanding and utilizing educational data.

## 3. FUTURE DIRECTIONS AND CONCLUDING REMARKS

The journey towards robust predictive models in online education is ongoing, and this study represents a significant step in that direction. The positive findings regarding early detection, model accuracy, and portability underscore the immense potential of applying data mining techniques to foster precision education. However, the limitations identified—such as the sample homogeneity and narrow focus on LMS behavioral data—suggest that further research is needed to validate and extend these methods in more heterogeneous educational environments.

In conclusion, the development of an early warning system for SPOCs using few-shot learning techniques represents a promising innovation for online education. By equipping educators with the tools to monitor and predict academic performance in real time, such systems not only enhance instructional effectiveness

but also contribute to the broader digital transformation of educational institutions. The insights generated from this study provide a robust foundation for future research aimed at refining predictive algorithms and integrating additional data modalities, ultimately advancing the field of educational data mining for the benefit of learners worldwide.

#### 4. MERMAID DIAGRAM: DATA COLLECTION, PREPROCESSING, AND MODEL BUILDING PROCESS

Below is a flowchart that outlines the end-to-end process followed in the study:

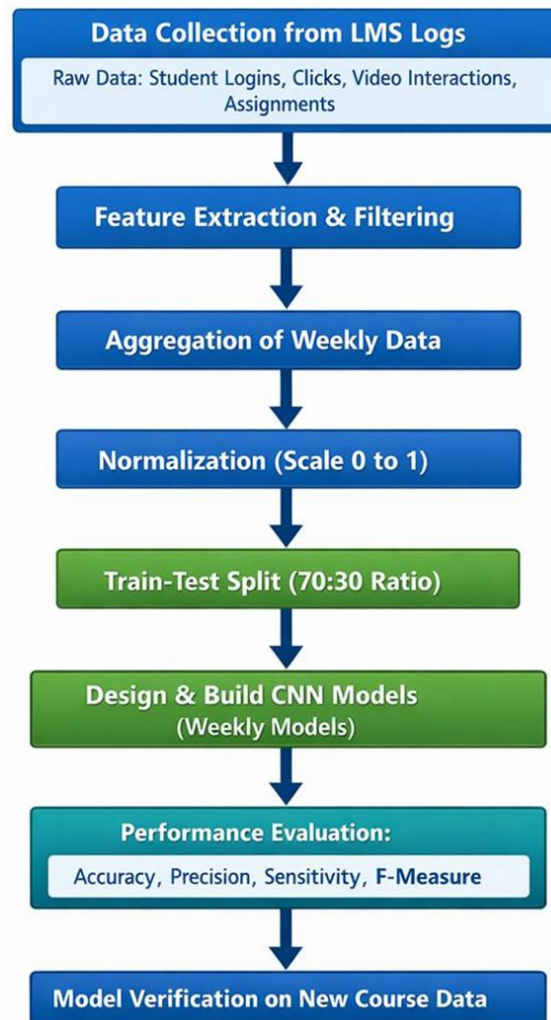


Figure 1: end-to-end process of study

The flowchart above visually represents the methodological steps from data extraction to the final verification of the predictive model's performance.

#### 5. FINAL SUMMARY OF KEY FINDINGS

- **Early Warning Capability:**  
Early prediction of student performance is achievable from week 5, providing a critical lead time for intervention.
- **Improving Accuracy with Time:**

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Accumulated LMS data enhances model accuracy, with performance reaching or exceeding 80% by week.

- **Portability and Sustainability:**  
The model demonstrates high portability, maintaining accuracy above 81% when transferred to a similar course, confirming the viability of few-shot learning approaches in consistent instructional settings.
- **Actionable Insights for Stakeholders:**  
Teachers, educational authorities, and IT directors can leverage these findings to foster precision education, allocate resources effectively, and drive the digital transformation of academic practices.

## REFERENCES

- [1] L. Jiang and G. K. S. Al-Shaibani, "Influencing factors of students' small private online course-based learning adaptability in a higher vocational college in China," *Interactive Learning Environments*, vol. 32, no. 3, 2024, doi: 10.1080/10494820.2022.2105901.
- [2] X. M. Zhang, J. Y. Yu, Y. Yang, C. P. Feng, J. Lyu, and S. L. Xu, "A flipped classroom method based on a small private online course in physiology," *Adv Physiol Educ*, vol. 43, no. 3, 2019, doi: 10.1152/advan.00143.2018.
- [3] M. K. Sharma, H. A. Alkhazaleh, S. Askar, N. H. Haroon, S. M. Almufti, and M. R. Al Nasar, "FEM-supported machine learning for residual stress and cutting force analysis in micro end milling of aluminum alloys," *International Journal of Mechanics and Materials in Design*, vol. 20, no. 5, pp. 1077–1098, Oct. 2024, doi: 10.1007/s10999-024-09713-9.
- [4] D. A. Majeed *et al.*, "DATA ANALYSIS AND MACHINE LEARNING APPLICATIONS IN ENVIRONMENTAL MANAGEMENT," *Jurnal Ilmiah Ilmu Terapan Universitas Jambi*, vol. 8, no. 2, pp. 398–408, Sep. 2024, doi: 10.22437/jiituj.v8i2.32769.
- [5] P. H. Nguyen, S. M. Almufti, J. A. Esponda-Pérez, D. Salguero García, I. Haris, and R. Tsarev, "The Impact of E-Learning on the Processes of Learning and Memorization," 2024, pp. 218–226. doi: 10.1007/978-3-031-70595-3\_23.
- [6] I. M. Putri, "ASUHAN KEPERAWATAN PADA TN.SI DENGAN CHRONIC OBSTRUCTIVE PULMONARY DISEASE (COPD) DI RUANG RAWAT INAP A RSUD KANJURUAN KEPANJEN," *Undergraduate thesis, Universitas Muhammadiyah Malang.*, vol. 14, no. 1, 2023.
- [7] Ç. Sıcakyüz, R. Rajab Asaad, S. Almufti, and N. R. Rustamova, "Adaptive Deep Learning Architectures for Real-Time Data Streams in Edge Computing Environments," *Qubahan Techno Journal*, vol. 3, no. 2, pp. 1–14, Jun. 2024, doi: 10.48161/qtj.v3n2a25.
- [8] Z. Arif Ali, Z. H. Abduljabbar, H. A. Tahir, A. Bibo Sallow, and S. M. Almufti, "eXtreme Gradient Boosting Algorithm with Machine Learning: a Review," *Academic Journal of Nawroz University*, vol. 12, no. 2, pp. 320–334, May 2023, doi: 10.25007/ajnu.v12n2a1612.
- [9] G. N. Vivekananda *et al.*, "Retracing-efficient IoT model for identifying the skin-related tags using automatic lumen detection," *Intelligent Data Analysis*, vol. 27, pp. 161–180, 2023, doi: 10.3233/IDA-237442.
- [10] M. Liu, "An IoT-Enabled Mental Health Monitoring System for English Language Students Using Generative Adversarial Network Algorithm," *Mobile Networks and Applications*, 2024, doi: 10.1007/s11036-024-02408-7.
- [11] Z. H. Chao, L. Yi, L. Min, and Y. Y. Long, "IoT-Enabled Prediction Model for Health Monitoring of College Students in Sports Using Big Data Analytics and Convolutional Neural Network," *Mobile Networks and Applications*, 2024, doi: 10.1007/s11036-024-02370-4.
- [12] R. Mahafdah, S. Bouallegue, and R. Bouallegue, "Enhancing e-learning through AI: advanced techniques for optimizing student performance," *PeerJ Comput Sci*, vol. 10, 2024, doi: 10.7717/PEERJ-CS.2576.
- [13] A. Albatat and K. J. Rustamov, "A Unified Multi-Layer Framework for Detecting and Mitigating Web Application Attacks in Cloud-Native Environments," *Qubahan Techno Journal*, vol. 1, no. 4, pp. 15–26, Nov. 2022, doi: 10.48161/qtj.v1n4a26.
- [14] N. Rustamova, R. Rajab Asaad, and D. Fayzieva, "Blockchain-Driven Security Models for Privacy Preservation in IoT-Based Smart Cities," *Qubahan Techno Journal*, pp. 1–17, Dec. 2023, doi: 10.48161/qtj.v2n4a22.
- [15] R. Asaad, R. Ismail Ali, and S. Almufti, "Hybrid Big Data Analytics: Integrating Structured and Unstructured Data for Predictive Intelligence," *Qubahan Techno Journal*, Apr. 2022, doi: 10.48161/qtj.v1n2a14.
- [16] J. A. Esponda-Pérez, M. A. Mousse, S. M. Almufti, I. Haris, S. Erdanova, and R. Tsarev, "Applying Multiple Regression to Evaluate Academic Performance of Students in E-Learning," 2024, pp. 227–235. doi: 10.1007/978-3-031-70595-3\_24.
- [17] J. A. Esponda-Pérez *et al.*, "Application of Chi-Square Test in E-learning to Assess the Association Between Variables," 2024, pp. 274–281. doi: 10.1007/978-3-031-70595-3\_28.
- [18] R. Rajab Asaad, R. Ismael Ali, Z. Arif Ali, and A. Ahmad Shaaban, "Image Processing with Python Libraries," *Academic Journal of Nawroz University*, vol. 12, no. 2, pp. 410–416, Jun. 2023, doi: 10.25007/ajnu.v12n2a1754.
- [19] R. Rajab Asaad, R. Ismael Ali, A. Ahmad Shaban, and M. Shamil Salih, "Object Detection using the ImageAI Library in Python," *Polaris Global Journal of Scholarly Research and Trends*, vol. 2, no. 2, pp. 1–9, Apr. 2023, doi: 10.58429/pgjsrt.v2n2a143.
- [20] S. M. Abdulrahman, R. R. Asaad, H. B. Ahmad, A. Alaa Hani, S. R. M. Zeebaree, and A. B. Sallow, "Machine Learning in Nonlinear Material Physics," *Journal of Soft Computing and Data Mining*, vol. 5, no. 1, Jun. 2024, doi: 10.30880/jscdm.2024.05.01.010.
- [21] A. B. Sallow, R. R. Asaad, H. B. Ahmad, S. Mohammed Abdulrahman, A. A. Hani, and S. R. M. Zeebaree, "Machine Learning Skills To K-12," *Journal of Soft Computing and Data Mining*, vol. 5, no. 1, Jun. 2024, doi: 10.30880/jscdm.2024.05.01.011.
- [22] S. M. Almufti, B. Wasfi Salim, and R. Rajab Asaad, "Automatic Verification for Handwritten Based on GLCM Properties and Seven Moments," *Academic Journal of Nawroz University*, vol. 12, no. 1, pp. 130–136, Feb. 2023, doi: 10.25007/ajnu.v12n1a1651.
- [23] S. M. Almufti, R. B. Marqas, Z. A. Nayef, and T. S. Mohamed, "Real Time Face-mask Detection with Arduino to Prevent COVID-19 Spreading," *Qubahan Academic Journal*, vol. 1, no. 2, pp. 39–46, Apr. 2021, doi: 10.48161/qaj.v1n2a47.
- [24] S. M. Almufti *et al.*, "INTELLIGENT HOME IOT DEVICES: AN EXPLORATION OF MACHINE LEARNING-BASED NETWORKED TRAFFIC INVESTIGATION," *Jurnal Ilmiah Ilmu Terapan Universitas Jambi*, vol. 8, no. 1, pp. 1–10, May 2024, doi: 10.22437/jiituj.v8i1.32767.