

A Review on Analyzing and Predicting At-risk Students by Means of Enhanced Deep Learning Models

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ABSTRACT

A critical job for guaranteeing at-risk students' academic achievement and wellbeing in educational environments is to identify and support them. Traditional techniques of identifying at-risk students frequently rely on subjective evaluations which can be labour-intensive, time-consuming. Researchers have looked into the possibilities of deep learning models in analyzing and forecasting at-risk students in light of the introduction of cutting-edge technology and the availability of large-scale educational data. The purpose of this review is to offer a thorough overview of the research on improved deep learning models for identifying and forecasting at-risk students. The review's conclusions suggested that a variety of Deep Learning (DL) techniques are employed to comprehend and resolve these problems, including identifying at-risk students and dropout rates.

Keywords

Machine Learning (ML), prediction of at-risk students, Deep Learning (DL)

1. INTRODUCTION

Massive Open Online Courses (MOOCs), Virtual Learning Environments (VLEs), and Learning Management Systems (LMS), which are rapidly advancing online learning platforms, have revolutionized education by removing the limitations of time and space while offering accessible and affordable learning opportunities [1]. These platforms produce enormous volumes of data that may be used to assess and analyze students' learning progress, giving educators new information and a better understanding of how they are performing [2]. It enables them to intervene, inspire, and direct students toward successful results and can help forecast their success in the future [3]. Deep Learning (DL) technology is now thought of as one of the trendiest topics in the disciplines of ML, AI and data science due to its capacity to learn from the provided data [4], [5]. DL can unearth important information that improves students' and instructors' knowledge. With the aid of this knowledge, educators can better tailor their methods of instruction, offer timely criticism, and provide focused assistance to students in order to maximize their learning opportunities.

Convolutional neural networks (CNN), artificial neural networks (ANN), recurrent neural networks (RNN), and generative adversarial networks (GAN) are examples of DL techniques [6], [7] that can be used to process and analyze the complex patterns found in the vast amounts of diverse data produced by online learning platforms. DL models give students the chance to discover important truths about how they learn. Students are better able to self-reflect, modify their studying strategies, and take charge of their academic achievement when they receive feedback and visualizations

that reflect their involvement, advancement, and performance patterns [8], [9]. Students that are self-aware will be more motivated and successful in their online learning experience overall. Although online learning platforms have created new educational opportunities, they also present special difficulties for teachers and students [10]. This review paper's primary objective is to thoroughly examine the various indicators and methods used to identify at-risk students. This paper focuses on the literature that plays vital role in online learning systems or educational platforms in improving or deteriorating the learning performance of a student. Also, the literature useful in understanding the drawbacks of existing online learning systems and to suggest possible solutions to overcome them using DL models. Authors are trying to identify the existing research gaps, limitations and challenges from recent literary works to assist the researchers who are conducting their research in this domain.

2. RELATED WORK

A prominent field of research has been the identification of at-risk students, and numerous efforts have been done to address this problem. CNNs, a kind of DL algorithm, are frequently employed in the analysis of student data and the identification of at-risk students. Recurrent neural networks (RNNs) were additionally employed to identify students who are at danger. RNNs are especially well suited for sequential data, such as students' cumulative academic records. They enable more precise forecasts since they may be used to capture temporal dependencies and long-term trends. Additionally, Generative Adversarial Networks have demonstrated promise in identifying students who are at risk. A generator network and a discriminator network that are in competition with one another make up GANs. [11] outlines a study methodology that identifies students at danger of failing computer programming projects by combining static and dynamic data from the students. This method's predictive models and tailored feedback have been shown to close the achievement gap between low- and high-achieving students and enhance exam results for students who adhere to the advice. The use of transfer learning from DNN to forecast students' performance in higher education is examined by Tsiakmaki and his colleagues [12].

Deep Learning is nothing more than a collection of interconnected classifiers built on linear regression and a few activation functions. The standard statistical linear regression approach serves as its foundation. The sole distinction is that DL uses multiple brain nodes as opposed to linear regression, which uses a single node in conventional statistical learning. Shallow learning and Deep Learning are the two distinct stages of machine learning development. Convolutional neural networks (CNNs), a subset of DL models, are designed primarily for processing organized grid-like data, such as

images or time series data [13]. Numerous computer vision applications, including image segmentation, object detection, and classification, have attracted considerable interest and shown great success using CNNs. Convolutional layers are a form of neural network architecture used by CNNs to automatically recognize and extract pertinent characteristics from incoming data. The structure and operation of the visual

cortex in the human brain serve as an inspiration for CNNs. The LetNet, AlexNet, and VGG architectures used by CNN are well-known. For instance, the LeNet-5 model [14] in figure 1, which was suggested to recognize 32*32 handwriting images, was made up of fully connected layers, two convolutional layers, and two subsampling layers.

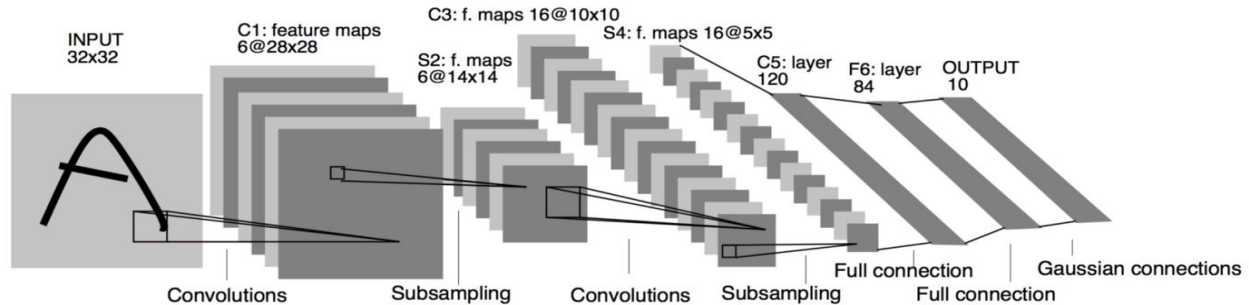


Figure 1 Figure from Gradient-based learning applied to document recognition, by Y. LeCun, L. Bottou, Y. Bengio and P. Haffner

In order to capture patterns and traits indicating student performance and risk factors, CNNs excel in automatically learning and extracting pertinent features from input data. By interpreting non-image data as having an image-like structure, CNNs can be used to analyze it. For example, time series data can be represented as 2D images, and text data can be represented using word embedding for text classification tasks. CNNs can handle multimodal data, combining several sources of input (including text, graphics, and structured data) to improve prediction and offer a comprehensive picture of student performance.

An ANN is made up of a set of tightly connected objects called Processing Elements. The network's design and functionality were inspired by the biological central nervous system, specifically the brain. Every Processing Element is designed to imitate a neuron, which in nature receives a weighted collection of inputs and generates the output that corresponds to those inputs [15]. The examples that follow show how ANNs have been used using different prediction approaches, usually by taking into account the results of student evaluations. A feed forward ANN was trained to predict assessment test outcomes using partial course scores. An ANN utilizing the cumulative grade point average predicted the academic success in the eighth semester. Through evaluations of the two ANN models, the most effective ANN model for predicting student academic progress was identified [16].

Another well-known neural network sends the output of the previous stage as input to the current stage using sequential or time-series data. Recurrent neural network (RNN) is the term used to describe this neural network [17], [18]. Recurrent networks, like CNN and feed forward, also learn from training input, but they distinguish themselves from other types of neural networks by having a "memory" that enables them to use data from past inputs to affect data from the present input and output. In contrast to a typical DNN, which assumes that inputs and outputs are independent of one another, an RNN's output is dependent on items that came before it in the sequence. On the other hand, the issue of declining gradients makes learning long data sequences difficult for conventional recurrent networks.

Long Short-Term Memory(LSTM) is a common RNN architecture that employs special units to handle the vanishing gradient problem. Three gates regulate the flow of data into and out of the memory cell of an LSTM unit, which has the ability to store data for lengthy periods of time. Since it addresses the issues with recurrent network training, the LSTM network is one of the most efficient RNNs. In both directions,

RNN/LSTM Bidirectional RNNs, which connect two hidden layers that run in opposite directions to a single output, enable the receiving of data from both the past and the future. Bidirectional RNNs may simultaneously predict both positive and negative temporal directions, in contrast to typical recurrent networks. The bidirectional LSTM, a.k.a. the BiLSTM, is an extension to the standard LSTM that can enhance model performance on sequence classification issues [19].

3. ROLE OF ONLINE LEARNING SYSTEMS OR EDUCATIONAL PLATFORMS

Discriminator networks and generator networks are components of a class of DL models known as Generative Adversarial Networks (GANs) [20]. The generator intends to produce realistic data samples, whereas the discriminator attempts to distinguish between actual and fake examples. Both of these neural networks attempt to outdo one other in a competition. In these circumstances, the weights of the generator learn, transforming a random noise vector into a model distribution. In Figure 2, Generator G extracts a random noise vector from latent space before producing any samples. Discriminator D now uses genuine training data as input and compares it to a fictitious sample produced by generator G. Images from tasks that are similar to the training data should be included, such as paintings, portraits, or other imagery. The error function returns a probability of whether the given sample is real or fake after taking both inputs. The generator and discriminator weights are both trained using this output. The formulation of the error function or cost function in GANs is an additional crucial component. Mini Max

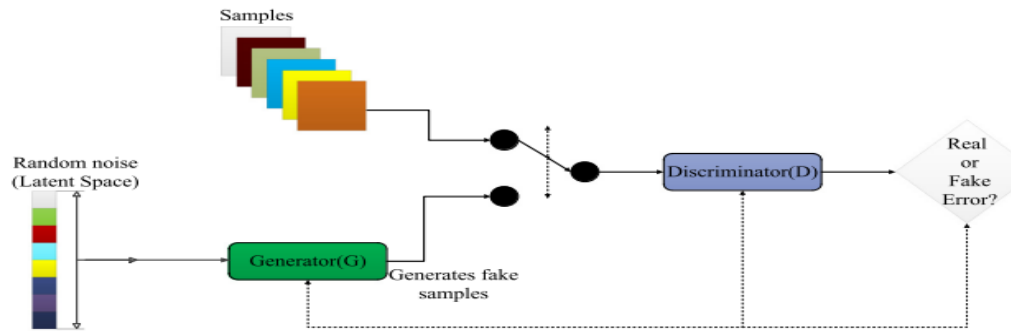


Figure 2. Generative Adversarial Networks works (Gast and Roth.2018)

zero sum game is how this issue is defined. The generator and discriminator are taught in an adversarial way using GANs [21], where they compete against one another to enhance their respective skills. GANs are well suited for jobs like picture synthesis, text generation, and music composition because they are primarily employed for creating new data samples that mimic the training data distribution. GANs can learn from unlabeled data because they don't need explicit labelling or training under supervision. By learning hierarchical representations, GANs can efficiently handle high-dimensional input, such as images or sequential data.

It is typical practice to use qualitative evaluation through visual examination to evaluate the quality of generated samples and find any flaws or artifacts. To assess the subjective quality, authenticity, and realism of generated samples, user studies with human evaluators can be carried out. Mode collapse [22], which occurs when the generator does not fully investigate the data distribution, might cause GANs to have a limited sample variety. Since existing metrics have drawbacks and might not fully reflect generated sample quality, research is still on-going to develop more thorough and trustworthy evaluation metrics for GANs.

Information and Communication Technology (ICT) has the potential to enhance student performance and allows teachers to assist students in completing assignments. As a result, high-quality instruction might be provided via virtual learning [23]. MOOCs are on the rise in higher education as a result of the recent ICT boom.

With the help of MOOCs, students get access to priceless online learning tools and data from around the globe. The issues with MOOCs' high attrition as well as low completion rates are also discussed in [24].

The [25] are focus on fusing clickstream data with a sophisticated LSTM model to predict students' academic success in online learning environments. The LSTM model surpassed cutting-edge techniques in the pass/fail classification challenge with 93.46% precision and 75.79% recall. The study obtained a 90% accuracy rate during the first 10 weeks of interaction between students in a virtual learning environment. The research supports the creation of long-term, student centered policies in higher learning and fosters student loyalty and trust. [26] talks about how challenging it is to identify at-risk students in online learning

environments. The suggested approach uses current courses to build a learning model and offers an XGBoost classification algorithm for categorizing risk in new courses. In order to identify at-risk students and facilitate early intervention, [27] investigates the use of deep artificial neural networks and

handcrafted features taken from clickstream data in virtual learning environments. The suggested approach outperforms the logistic regression and support vector machine models, achieving classification accuracy of 84% to 93%.

4. TIMELINE OF THE KEY RESEARCH

The features of the literature review are prepared based on the objectives, applications, results and future works obtained from existing literary works is shown in table 1.

Table 1. Summary of the main features of the literature review

Author	Objectives	Methodology used
Barbosa, A. M., et al., (2017)[28]	Student dropout prediction	Classification with reject option paradigm
M. Hlosta, D. et al., (2018) [29]	monitoring student behavior in online learning	General Unary Hypotheses Automaton and Markov chain-based analysis
Pereira, F. D., et al., (2020) [30]	Early prediction of students' performance in programming courses	Deep Learning ,Evolutionary Algorithm
Hussain, S., et al., (2019) [31]	Analyzing academic performance using DL and linear regression	Deep Learning, Linear Regression
Xing, W., & Du, D. (2021) [32]	Optimize dropout prediction for at-risk students	Deep learning (Temporal model)
Kusumawardani, S. S., & Alfarozi, S. A. I.(2023) [33]	Sequentially predict students' final performance in learning management systems (LMS)	Transformer Encoder (Deep Learning)
Lottering, R., et al., (2020)[34]	Identifying at-risk students	RF,SVM,RF,DT Naïve Bayes, K-Nearest Neighbor, LR
Chen, Y.; et	Early	Survival

al.,(2018)[35]	identification of at-risk students	analysis, logistic regression, decision trees, boosting
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Key findings of the research presented by [28] are Successful three-group classification, vigilant supervision, validation with the Rejection curve, the counselling hypothesis was confirmed, and the usefulness was resource-limited. Authors are trying to obtain more datasets to evaluate the approach's generalizability and carrying out a thorough longitudinal study on students who were rejected to gauge the efficacy of intervention tactics. [29] were examined GUHA and Markov chain models in order to get insight into how students behave in an online learning environment. Authors suggest future work to Investigate student behavior patterns to help predictive models get better, and use Markov chains to organize interventions. [30] developed DL pipeline performs better at forecasting student achievement than the old model and suggests to analyze students whose actions are changing and consider adjusting your methods for improved outcomes. [31] suggests that Smaller datasets also produced superior results, indicating the potential of DL in educational data mining real-time recommender and also predict and also predict that DL surpassed linear regression in predicting academic achievement of college students in India. [32] predicted in MOOCs, the accuracy of dropout prediction models is improved by DL algorithms. For individualized intervention, individual student dropout probability can be generated and suggested to use the actual MOOC courses as a testing ground for the proposed prediction model and intervention customization technique. Similar research should be done on more general online courses to determine whether DL is applicable in various educational settings. [33] At least 76% of at-risk students were correctly predicted by the model and Use the suggested approach for other LMSs with comparable data architectures. [34] gives 94.14% accuracy rate in their research study and predict that the Random Forest had the best results in detecting dropout-risk students. [35] Effectively identify at-risk students, forecasting dropout time, and emphasizing significant variances are the goals of survival analysis. They try to Improve graduation rates by incorporating suggested strategies into degree planning and early warning systems.

5. LIMITATIONS, CHALLENGES AND RESEARCH GAPS

From the literature review, several limitations, challenges, and research gaps can be identified in the prediction of at-risk students using DL algorithms and related techniques. These includes:

The lack of labelled data for developing prediction models is a typical problem. It can be challenging to collect labelled data for at-risk students because doing so entails monitoring students over time to determine which ones eventually develop risk factors. In this subject, acquiring a suitably sizable and representative dataset continues to be difficult. Due to their intricate architectures, DL algorithms such as CNNs and RNNs are frequently referred to as "black-box models." It can be difficult to interpret and explain the predictions that these models produce. To win over the confidence and understanding of educators and stakeholders, it is essential to develop approaches that offer insights into the variables leading to the prediction of at-risk students. For accurate predictions, strong techniques must be developed to address these issues. While

accurately identifying at-risk students is important, the ultimate objective is to intervene and help these students. It is still difficult to bridge the gap between predictive models and practical solutions. To improve student outcomes, future research should concentrate on fusing tailored intervention techniques with prediction models. To assess the effectiveness of various prediction models, defined evaluation measures and benchmarks are required.

6. CONCLUSION

In summary, using cutting-edge deep learning approaches has produced encouraging outcomes in identifying and forecasting at-risk students in educational contexts. The comprehensive analysis of the literature revealed the wide variety of deep learning models and approaches used to address the difficulties in identifying and assisting at-risk students. These models have proven successful at identifying at-risk students and dropout rates, enhancing overall student performance. However, a number of significant issues and research gaps have been found. Future study must address issues like the lack of labelled data, model interpretability, generalizability, imbalanced datasets, ethical constraints, and the requirement for longitudinal data analysis.

7. FUTURE SCOPE

The development of methods for handling unbalanced datasets, improving model interpretability through attention mechanisms or explainable AI strategies, and investigating novel deep learning architectures designed for at-risk student prediction should be the next priorities. when deploying deep learning models in educational environments, ethical issues including fairness, bias, and student data privacy must be carefully examined and taken into account. In general, the use of advanced deep learning algorithms has the potential to change the systems for identifying and assisting students who are at risk, allowing for prompt interventions and promoting their academic achievement. Researchers and educators can work toward more precise, equitable, and comprehensible prediction models that have a beneficial impact on student achievements and well-being by addressing the current difficulties and research gaps.

7. AUTHORS' CONTRIBUTIONS

All authors contributed to the research design and development, discussed the results and contributed to the final manuscript.

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