Transforming Education with Deep Learning: A Systematic Review on Predicting Student Performance and Critical Challenges

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Abstract

Deep learning (DL) is recognized as a breakthrough in the educational technology arena, more so in the sense that it can be applied for forecasting student performance and critical issues in academic systems. This systematic review is used to investigate advances in the DL-based system-to-predicting student performance and emphasizes its applicability, methodologies, and limitations. The paper analyses key technologies such as neural networks (NNs) and ensemble models used in educational data mining. The paper also points out limitations in previous studies, for example, data imbalance model interpretability, and issues of scalability. This review highlights the potential of DL to improve educational quality, provide personalized learning experiences, and mitigate learning hazards by synthesizing ideas from different studies. Future directions will comprise hybrid models, improvements in data preprocessing, and merging with real-time educational systems to optimize the performance of the prediction model in several academic environments. For this review, 58 papers were collected from the year 2017-2024 respectively based on DL in education, Risk in education, and student education performance analysis. Subsequently, the aim, technique used, dataset used, performance score attained, significance, and limitations of the existing studies were discussed in this review.

Keywords: Education; Student Performance Evaluation; Artificial Intelligence; Predictive Modeling in Education; Academic Analytics; and Learning Outcome Prediction

1. Introduction

DL, which enables the provision of predictive analytics, adaptive assessments, and personalized learning experiences, has, in recent years, emerged as a game-changing tool in education [1]. DL, a branch of AI, mimics the NNs found in the human brain for detecting patterns and make predictions. It has shown promise in predicting student performance, finding learning gaps, and suggesting customized interventions in the field of education [2]. The huge volumes of data that students' interactions produce allow DL algorithms to discover patterns that may elude traditional approaches, so teachers can pinpoint problems more precisely [3]. DL has reached advanced levels in some major areas, such as forecasting student performance. Based on the analysis of demographic information, behavioural patterns, and prior academic data, the DL model can predict different individual student outcomes: including grades, dropout risk, and overall academic performance. Thanks to this predictive power, teachers will be able to intervene proactively in the lives of kids who are on the verge of performing below potential and provide support timely. Furthermore, these models can be better as new data can be collected more and more so as time accuracy increases also leading to a better approach toward teaching methods [4].

Another important benefit of the applications of DL is that it can fill all the gaps in important educational needs. Traditional methods of educational assessment often overlook essential non-cognitive elements that often affect learning outcomes significantly; these include motivation, engagement, and socioeconomic background [5]. The predictions that DL models come up with can accommodate all these factors, providing more holistic needs for students' understanding. This skill enables fair implementation of educational interventions. As a result, the process

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ensures that each kid regardless of background receives proper care to thrive. Although it is potential, some challenges occur when implementing DL in the classroom. These challenges include the interpretability of the DL model, demand for quality datasets, data protection issues, and investment into infrastructure and teacher preparation before these technologies can be put to use. This paper attempts to discuss these problems and highlight the potential of DL in enhancing learning outcomes, particularly in the areas of forecasting student performance and filling in important learning gaps.

A. Scope of the Review

This review study focuses on the use of DL methods to forecast student performance and close important inequalities in educational outcomes. A variety of DL models has been used for large-scale student data analysis, including CNN, LSTM, and RNN. It is presented against the backdrop of multiple applications on various datasets comprising behaviour, demographics, and data from learning management systems that discuss the potential use of such models for different predictive measures of academics such as grades, dropout rates, and at-risk students. In conclusion, it suggests possibilities in DL towards making intervention earlier and offering learning more personal.

B. Motivation

This paper was inspired by the escalating demand for data-driven solutions to the problems that modern systems of education face—first, in the forecasting and improvement of performance levels for students. The massive rise of produced educational data opens a broad door for using DL models for deriving relevant and practical insights to be useful in teacher decision-making. This review of DL's ability to predict students' outcomes and identify their knowledge gaps, moves forward in building more effective, personalized, and fair teaching approaches. In this regard, the review provides an exhaustive overview of the art in this industry as it reflects on the challenges surrounding the practical implementation of such sophisticated models including data privacy concerns, model interpretability, and the quality of available datasets.

C. Objectives

- Initially, data has been collected from the relevant academic records
- Pre-processing has been carried out the collected data to clean and pre-process the collected data to handle missing values, outliers, and inconsistencies.
- Subsequently, required features were selected by using DL models such as CNN, LSTM, and RNN.
- To select the required features by LSTM or RNN for sequential data and CNN for spatial or image-related data and the education performance analysis has been carried out by a DL approach.
- Finally, performance has been measured to validate the performance attained by the suggested model.

2. Methodology

A. Method for SLR on DL in education and student performance analysis

B. Search strategy

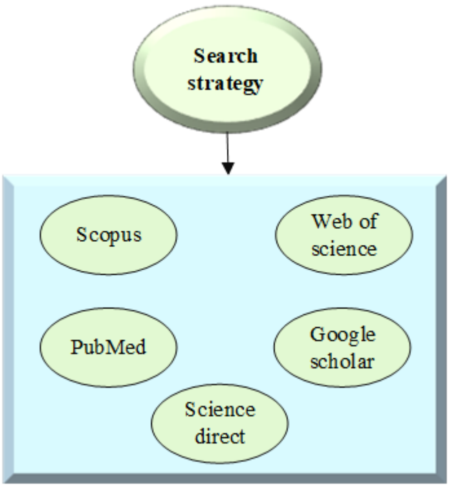

Figure 1. search strategy

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C. Inclusion Criteria

a) Publication Date: Articles published between 2017 and 2024.

b) Language: Articles must be published in English.

c) Content Relevance: Research focusing on certain facets of the DL in education and student performance in education

d) Types of Publications: Peer-reviewed journal articles, conference papers, and official reports.

e) Focus Areas: Research that includes discussions of DL in education, Early Detection, and Intervention for At-Risk Students, Transforming Teaching Methodologies through Predictive Analytics, Evaluation of Student Performance Prediction Systems and Enhancing Academic Support Systems and Student Assistance

f) Methodology: Both qualitative and quantitative studies.

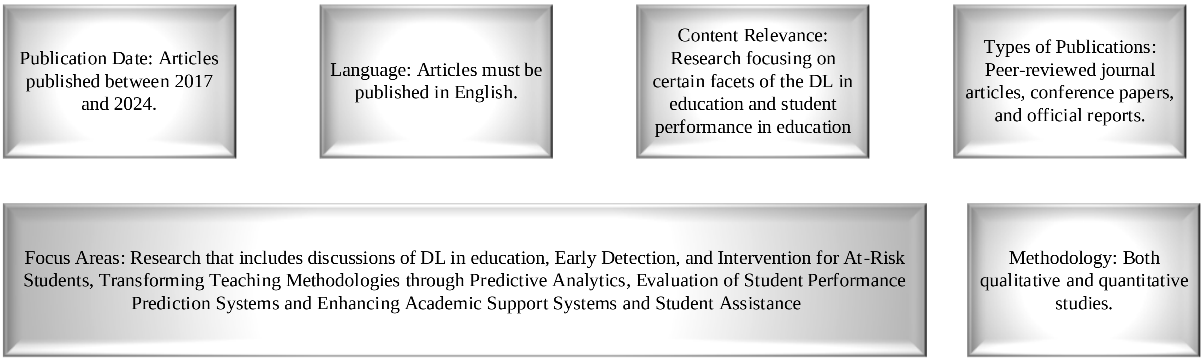

Figure 2. inclusion criteria

D. Exclusion Criteria

a) Publication Date: Articles published before 2016.

b) Language: Articles not published in English.

c) Content Relevance: Studies that do not specifically address DL-based education and performance analysis of students

d) Types of Publications: Non-peer-reviewed articles, opinion pieces, editorials, and non-scholarly publications.

e) Focus Areas: Research that does not contribute to the education in DL and student performance analysis based on DL

f) Methodology: Studies lacking a clear methodological approach or not providing empirical data

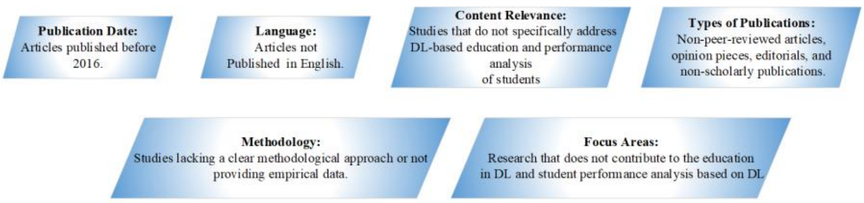

Figure 3. exclusion criteria

E. d. Keywords and Boolean Expression

"Artificial Intelligence in Education" AND, "Deep Learning Applications" OR "Deep Learning Algorithms" AND "Student Performance Evaluation" OR "Predictive Modeling in Education" AND "Academic Analytics" OR "Learning Outcome Prediction".

F. Data Extraction:

- Article Information: Title, authors, journal, publication year.
- Study Focus: Key themes such as DL in education and DL-based approaches for student performance analysis

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- Methodology: Qualitative or quantitative approach, data sources, analysis techniques.
- Findings and Conclusions: Main findings related to the DL based education and performance analysis using DL approaches

G. Quality Assessment

- Each study was evaluated for quality and relevance using criteria such as,
- Clarity of research questions and objectives.
- Appropriateness of the methodology.
- Robustness of data analysis and interpretation.
- Relevance to the circular economy in textiles.
- Contribution to the field.

H. PRISMA flow chart

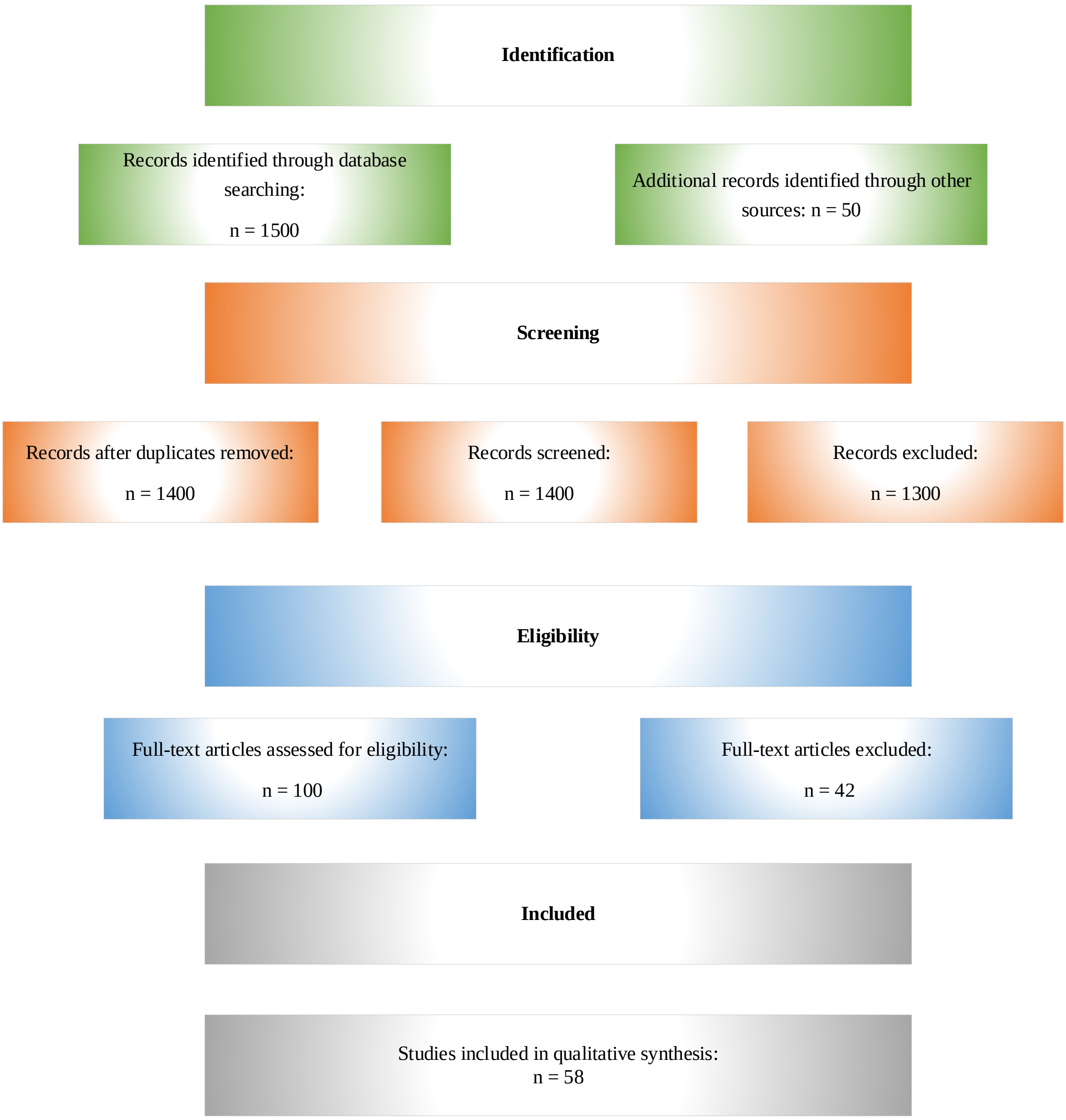

Figure 4. PRISMA flow chart

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Figure 1 is the search strategy 2 & 3 shows the study inclusion and exclusion criteria and the following Figure 4 is the PRISMA flow chart.

3. Early Detection and Intervention for At-Risk Students

[6] suggested a 5-stage probabilistic logistic regression (LR) model that identifies at-risk students throughout the school term. With student engagement, demographic, and performance data, the model predicts the probability of failure on subsequent tests. The highest accuracy was achieved at 92.81% in week 6, with lower uncertainty in later stages. The results indicate that performance statistics outweighed engagement and demographic considerations. This method helps teachers make timely interventions, thus improving academic outcomes. [7] developed a study based on risk students are identified by using an XAI together with the system applying the concept based on academics, personal, and soft skills data. The whole system was trained on data collected from a school district; it offers continuous tracking along with deviation notifications; therefore, it allows very effective proactive interventions to aid students' progress. Therefore, this is a scalable innovation that can help at-risk pupils and results show academic improvement along with well-being. [8] suggested XAI to Measure Student Performance. It has been possible to identify characteristics influencing student achievement by making use of the OULAD and SHAP methods. By a combination of ML & DL models, the study predicts performance with an accuracy of 94%. Engagement and registration deadlines are the main variables. SHAP gives information on particular aspects contributing to success or failure. The results can be helpful to educators in formulating focused interventions for improved outcomes in online learning environments. [9] suggested SPPA methodology allows teachers to detect at-risk students and provide interventions without any strong institutional investment. The pedagogical concepts are assimilated by using course-specific data and bridging the knowledge gaps through personalized interventions. In a large-scale test of a course, SPPA demonstrated excellent prediction capability and enhanced results. It simplifies learning analytics for teachers and fosters higher usage of interventions. Positive feedback from early users suggests that it can scale in higher education. [10] introduces an ensemble of machine learning predictors for the forecasting of student achievement using both historical and up-to-date data. Digital footprints, academic records, as well as personality profiles, hybridize this approach. Ensemble prediction resulted in very good accuracy about semester success at Siberian Federal University. This transferable approach will work similarly in other institutions to use as a foundation for integral predictive modelling. Findings take into consideration scalability and expanded instructional insights.

[11] suggested MCPD model predicts student achievement with the integration of textual teacher comments and numerical grade data. Independent encoders and attention processes identify nonlinear behavioral changes, enhancing the model's ability to be more accurate in its predictions. A 70-75% accuracy rate beat baselines, and the model showed transferability with at-risk criteria. A multimodal analysis provides actionable information for timely intervention and improves the strategy in understanding and grasping student behavior as well as academic risk. [12] used predictive analytics to detect poor-performing computer science students using second-year results. The models accurately detected key courses whose performance determined overall results with an accuracy of 96%. A big dataset of 430 students meant that there was enough space for a holistic analysis with remedial action to strengthen outcomes. Findings make a good template for future breakthrough in forecasting. This approach enhances educational practice and decision making by stakeholders. [13] suggested DL for Classification of At-Risk Students. DL models (vRNN, LSTM, and GRU) graded students as pass or fail using the LMS activity. The best accuracy was obtained with GRU on datasets of King Abdulaziz University at 98.90%. Recall for at-risk students was 81% with variability between datasets. This sustainable pipeline is the first step toward a long-term future that sophisticated models can use to detect and support at-risk children. The results are scalable and effective. [14] used ML models that predict student withdrawals from VLEs. Comparing other strategies, random forests outperformed other in finding important factors such as involvement in courses. Findings show the need for the data of VLE's early intervention. These educators to provide tailor-help, thus reducing dropout rates, can use the results. The study emphasizes the need for predictive analytics in virtual education. [15] suggested AI for Enhanced Educational Outcomes. AI-powered learning analytics technology is transforming education by identifying pupils in danger of failing early. Models that are created from various datasets reflect engagement, academic success, and personal characteristics. DL, explainable AI, and hybrid models offer scalable and reliable predictions. These tools allow instructors to act more effectively, thereby improving outcomes. The study opens the way for novel and useful applications of AI in education.

[16] suggested Establishing an EWS. It makes use of an Early Warning System for dropout prediction based on socio-cultural and educational characteristics. Detailed dropout indications are found in a specialized database. In this work, the KNN model had training and testing accuracy greater than 99.5% and 99.3%, respectively. The Django application illustrates the findings to support planning education. This tool can increase precision about student dropout problems. [17] Used dropout risk from machine learning identified 14,495 undergraduates (8.5% dropout rate). Dropout precision was enhanced by more than 50% using Threshold Probability in Random Forest. Academic performance, age, funding, and the proficiency of the English language were key factors. Retention

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percentages were above 70% and drove the academic programs. The model achieves an effective balance between dropout and retention precision. [18] suggested the Impact of COVID-19 on Academic Performance. The pandemic disrupted the students' study patterns, hence performance. Regularized ensemble learning improved the predictions based on the data from the COVID era. Pruned Random Forests were used to deal with outliers. Attendance, contact, and connectedness were major contributors. This technique detects at-risk pupils, hence improving interventions. [19] discussed a dropout prediction framework for MOOCs. Dropout rates of up to 90% characterize MOOCs. The framework here employs recurrent NNs to predict dropout, then it builds behavior patterns. It develops better intervention strategies using the OLAP module. Useful projections are developed for the weekly outcome. Thus, the system improves the engagement levels of learners for MOOC. [20] discussed about LANSE: Learning Analytics Tool. LANSE is cloud-based and predicts dropout as well as failure risks in learning management systems. Weekly machine learning predictions help visualize the students' performances. Distance learning interventions are optimally applied when used first.

[21] developed personalized feedback from early warning systems. Predictive models will use LMS data for at-risk and excellent performers. RF had 78.2% accuracy for the high achievers, but LSTM has early prediction ability. Static LMS logs produce reliable predictions of outcomes. Clear protocols and accountable policies improve the real-world application. [22] using Attention-Based ANN to Forecast Performance. Attn-ANN analyzes time and feature dimensions using attention weights to predict the achievement of students. It performed better than standard algorithms in an ablation investigation. Real-world interventions of the model are useful in the visualization of the model. Attention-ANN connects predictive insights with educators' knowledge. [23] suggested complementary CatBoost for Prediction: C-CatBoost boosts prediction as it uses residual errors to estimate them. It outperformed the other models by up to 18%, with RMSE of 1.1099 on Mathematics and 1.0246 on Portuguese. This complementary technique enhances the quality of prediction, which in turn helps in enhancing educational quality. [24] proposed a time-series analysis with multiple dimensions. Such a performance model utilizing multi-dimensional data shall be able to identify an at-risk pupil early enough. In OULAD, it scored 99.08% accuracy concerning the early risks. Very valuable information was obtained from both the learning behaviour and demographics. This helps in individualizing treatments that cater to differing needs among students. [25-26] developed risk prediction methodologies. The dropout prediction accuracy improves by 2-4% with heterogeneous ensemble approaches. CRISP-DM technique proves the importance of features in LMS data. The ensemble approaches are better than classical classifiers. The results show the significance of ensemble learning in dropout strategies. The overall summary of these research works is manifested in Table 1 and Figure.5, respectively.

Table 1: Summary of Studies on Predicting At-Risk Students

Author(s)	Technique Used	Dataset Used	Performance Score	Risk Factors Found	Limitations
Nimy et al. 2023	PLR	Moodle Data, Demographic Data, Student Performance Data	Accuracy: 92.81% (Week 6), Uncertainty decreased by 60%	Student engagement, Demographics, Assignments, Tests	Lack of comparison with other models, Limited to Moodle and demographic data
Embarak & Hawarna, 2024	XAI, Multi-modal Approach	School District Student Data	High accuracy (specific score not mentioned)	Personality, Academic Performance, Soft Skills	Pilot study, Dataset limited to a specific district
Ujkani et al. 2024	ML & DL SHAP (XAI)	OULAD	Accuracy: Up to 94%, SHAP for interpretability	Student engagement, Registration timelines, Course registration	Limited to OULAD, may not generalize well to other institutions

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Alalawi et al. 2024	SPPA	Undergraduate Course Data (historical assessments)	High accuracy in predicting at-risk students	Gaps in knowledge, Risk levels, Personalized study plans	Limited scalability, Needs large-scale institutional support
Kustitskaya et al. 2024	Hybrid ML Models, Ensemble Models	Siberian Federal University Data (Digital footprint, etc.)	High forecast quality (specific score not mentioned)	Academic performance, Engagement, Educational environment	Limited to one university, may not generalize across institutions
Cheng et al. 2024	MCPD	Middle School Teacher Remarks & Grade Data	Accuracy: 70-75%, outperforming baseline algorithms by 5-10%	Behavioral changes, Academic grades, Teacher remarks	Limited to one grade level, Generalizability uncertain
Qushem et al. 2024	Predictive Analytics, ML, Multi-method Approach	Computer Science Degree Performance Data (University)	Accuracy: 88% (Course grades), 96% (All course grades)	Course grades, Academic performance	Focus on one major, Specific to university data
Al-Sulami et al. 2023	DL (vRNN, LSTM, GRU), Supervised Learning Approach	LMS Activity Data from King Abdulaziz University	Accuracy: GRU (93.65%, 98.90%), Recall = 81%	LMS activity, Online engagement, Final grade prediction	Limited to one institution, May not generalize to other LMS platforms
Zhang et al. 2024	RF	Open VLE Dataset	RF outperforms other models	VLE activity, Withdrawals, Engagement	Dataset from open VLE may not reflect all institutions' data
Javed et al. 2024	ML based (Feature Engineering & Analysis)	University Learning Data (Online learning activity)	Accuracy: 90% (Triple-class), 94.8% (Binary-class)	Online learning data, Feature engineering, Resampling techniques	Limited to university data, May need more data types to improve accuracy
Skittou et al. 2023	KNN Algorithm	Original database	Accuracy: 99.5% (Training), 99.3% (Test)	Socio-cultural, structural, educational factors impacting dropout decisions	Limited to the available data, lack of generalizability to other institutions

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Gonzalez-Nucamendi et al. 2023	RF, Threshold Probability	14,495 undergraduate students	Accuracy: 13.2% (Dropout), 99.4% (Retention)	Academic performance, prior grades, entrance exam scores, student age, etc.	Limited dataset size, class imbalance
Khan et al. 2024	Regularized Ensemble Learning	University students, online learning data	Best performing pruning strategy	Class attendance, internet connectivity, prerequisites, student interaction	Limited to online learning context, may not generalize to face-to-face learning environments
Mourdi et al. 2023	RNN	MOOC learner data	Not specified	Learner behaviours, course navigation patterns	Limited visibility on real-time progress, unclear dropout predictions
Cechinel et al. 2024	Machine Learning (Cloud-based)	LMS data	Not specified	Student behaviour's, course interactions, engagement	Privacy concerns, real-time processing challenges
Santos et al. 2023	RF, Extremely Randomized Trees	Information Management school data	AUC: 0.756 (At-risk), Accuracy: 78.2% (High-performing)	LMS logs, course data, student clicks	Implementation challenges for real-time predictions, need for policy protocols
Leelaluk et al. 2024	Attention-Based ANN	Not specified	Better AUC scores than conventional models	Lectures, learning activities, time duration	Not clear on scalability or integration into existing systems
Fan et al. 2024	Complementary CatBoost (C-CatBoost)	Student performance data	RMSE: 1.1099 (Math), 1.0246 (Portuguese)	Course grades, subject-specific performance	Limited to specific subjects, does not cover diverse learning activities
Shou et al. 2024	Multidimensional Time-Series Data Analysis	OULAD	Accuracy: 74% (Four-category), 99.08% (Early risk)	Learning behaviours, assessment scores, demographic information	Lack of specificity on handling multi-class tasks, may not generalize to other datasets

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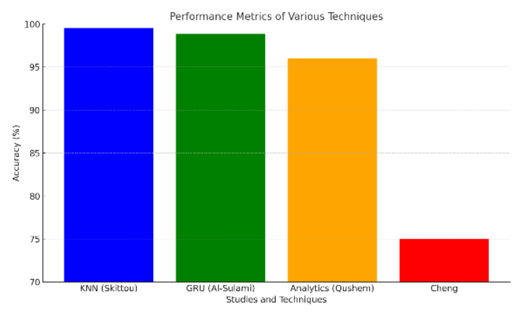
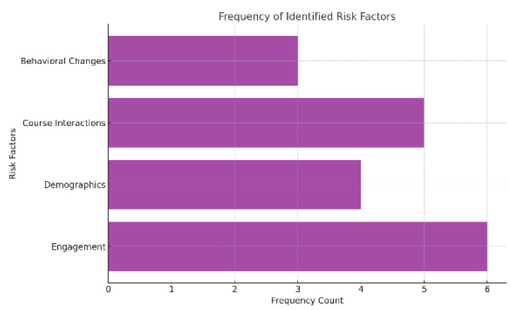
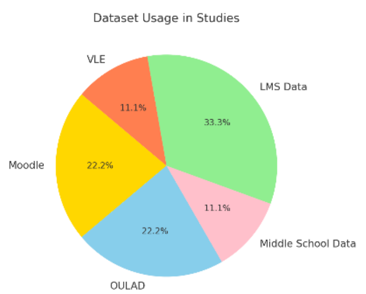
Pecuchova & Drlik, 2023	Voting-based Heterogeneous Ensemble (AdaBoost, XGBoost)	University Learning Management System data	Improved by 2-4% over traditional methods	Student interaction, course performance metrics	Ensemble methods may introduce additional complexity in real-time applications and data handling



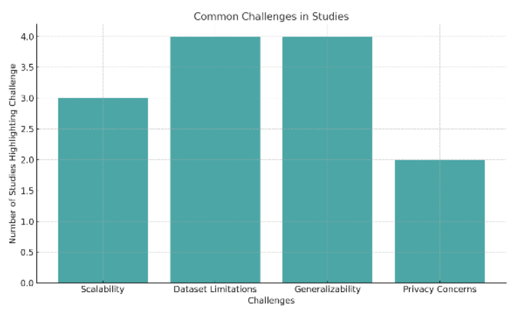
Performance Metrics of Various Techniques



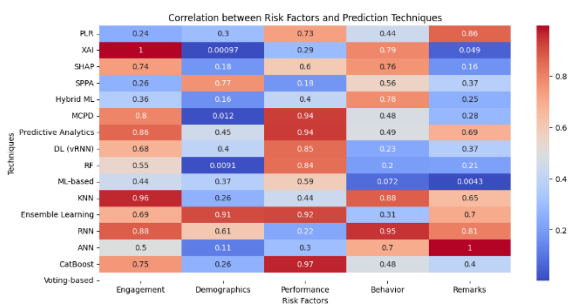
Frequency of Identified Risk Factors:



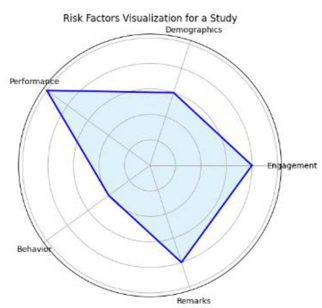
Dataset Usage in Studies



Common Challenges in Studies



Correlation between Risk Factors and Techniques



Risk Factors per Study

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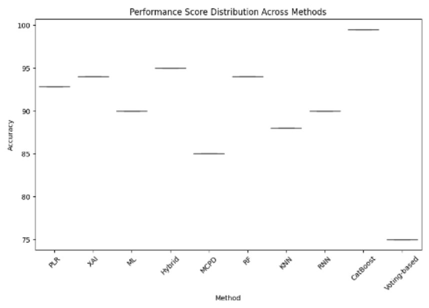

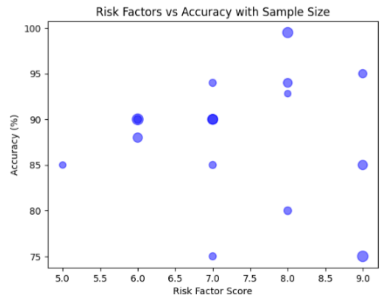

Performance Score Distribution Across Methods	Risk Factors vs Accuracy

Figure 5. Analysis on the SOTA approaches [58]

4. DL in education performance

[28] suggested student Performance Analysis Using BP-NN. A Student Attribute Matrix, SAM, was developed for quantifying student traits for performance analysis. BP-NN predicted students' performance based on the prior knowledge and peer's traits. The article further provided measures of student growth and potential. These technologies were applied to data for 60 high school students. The results showed the correct predictions and insights regarding the progress of students. [29] using of ICT and LMS in teaching. The study explored Moodle plugins for analysing student engagement and success in higher education. It analyzed the relationship between student activity logs and final grades. It found that gender was associated with performance but not with material selection. There is a significant relationship between the log frequencies to achievement of higher grades. This research aimed to utilize LMS as a predictive factor for bettering student's performances. [30] continued using DT algorithms like J48, Random Tree, and REPTree. The predictions were made regarding student performance with the help of survey data on health, social activities, and academic characteristics. The J48 algorithm achieved the best result. 161 surveys were analysed using Weka 3.8 software. The model recommended data mining for the discovery of elements that enhance student performance. It was suggested that a decision tree-based method could be used for improved performance prediction.

[31] applied ANNs to clickstream data gathered from virtual learning environments. The model outperformed logistic regression and support vector machines, with 84% to 93% accuracy classification results. Legacy and assessment data were the most relevant to the model. Predictive performance was based on a student's engagement style and interaction with previous lectures to predict student achievement. Early school-based intervention was to be supported by the study.[32] suggested video-based learning in combination with flipped teaching was used to predict student achievement. Data from learning management systems, mobile apps, and student information systems were processed using categorization algorithms. Feature reduction methods used included genetic search and PCA. Random Forest was the most accurate predictor, with an 88.3% rate. The study aimed at the significance of video learning analytics in enhancing educational outcomes. [33] compared several ML models for the prediction of student performance in MOOCs: Linear Regression, LR, RF, and K-NN. Demographics, academic background, and course interaction were included in the data. The accuracy of the Random Forest model was over 77%. Findings suggested that data can be used to improve MOOCs. [34] suggested the two-stage data mining algorithm predicted the performance of students using first-year academic data. The methodology segregated pupils into groups based on early indications of failure or high performance. RFs outperformed other classifiers with an accuracy higher than 95%. The methodology helped in identifying pupils at risk of failure and allocated resources better. It aimed at raising the general level of achievement while reducing failures. [35] suggested about Modelling neuronal network for students' performance. To predict students' performance, the author employed NNs models coupled with standard statistical analysis. It had 11 input variables and was trained via Levenberg-Marquardt technique. The result produced by the model in accuracy was 84.8%. The paper exemplifies the efficacy of NN in performance prediction. In spite of some flaws found in the model, its potential for educational outcome predictions is highly significant.

[36] suggested data mining techniques are being used with increasing frequency in education to throw light on significant learning behavior. These strategies help schools study the performance of students as well as track trends. Typically, classification is a strategic approach for predicting student performances, which enables institutions to make judgments. The results show that the hybrid strategy outperforms traditional methods in forecasting the outcome of students. [37] suggested Student Performance Prediction using DL Application. With

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the DL ability, teachers and management will monitor and follow the pupil through reduced chance for failing the academics or even expulsion. It uses the labelled features, hidden layers with feed forwarding, and backpropagation, hence the application of DNN on prediction. It is one with promising results that indicate that it would work in terms of predicting the academics since MAE 0.593 and RMSE 0.785 was recorded. [38] uses DL to predict student success in mathematics and Portuguese courses while also solving data imbalance using SMOTE. The proposed DL model resulted in excellent performance after the evaluation using precision, recall, F-score, and accuracy, with an accuracy of 0.964 for Portuguese and 0.932 for mathematics. Both courses have a 0.99 and 0.94 precision rating, which makes such a model suitable for early forecasting of performance. Nabil et al. (2021) presented a study on predicting Student Performance in the Early Semester. Early student success prediction plays a critical role in high education, especially in complex concepts such as programming and data structures. EDM mines learning data for performance forecasting of students and finding at-risk of failure students. The approach uses various models that include DNN, DT, and SVM classifiers on data from a public university. Its overall accuracy reached 89% above other competing models and illustrated the effectiveness of the prediction of the student's attainment for early use in the term. [39] predict student academic performance based on historical data. The enhanced feature extraction in this model increases the accuracy for the prediction task and is scored at 90.16%. Results demonstrate that with attention, BiLSTM outperforms traditional approaches and offers useful information to educational institutions. The analysis on the existing approaches on DL in education is manifested in Figure.6.

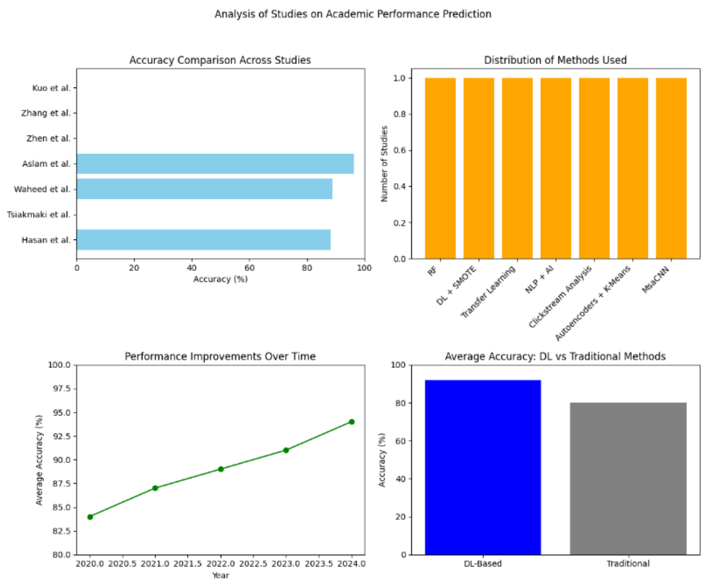

Figure 6. analysis on the SOTA approaches on DL in education [56]

[40] focus is on the effectiveness of DNN transfer learning for the prediction of student success in higher education. Experiments with data from five mandatory undergraduate courses showed that the use of transfer learning is effective in predicting student performance when relevant course data are available. [41] suggested the evaluation of flow state in e-learning settings. E-learning environment help us understand their involvement and problems by evaluating the flow state of the students. In the flow theory-based approach of assessment for students' flow state by analysing interactions from e-learning platforms, activity heat maps, and DNNs; it combines the information along with the statistical analysis, leading to determining and validating flow states using the information. Its utility on a multi fact is testimony to the fact that feedback mechanisms using the proposed method have allowed wide usage for supporting both instructors and learners in online learning. [42] combines student data and results from courses to predict student success and provide early counsel to the at-risk students. Using the K-Means algorithm, the study group's courses for better prediction accuracy. The pre-training of NNs on Denoising Auto-encoder is done for every course, and these models are merged into the ensemble predictor to achieve continuously growing accuracy through online learning. [43] employs a NN model to predict student performance based on a dataset of 131 individuals and 22 variables. The accuracy of the model is drastically improved when using the Adam optimiser, reaching over 96% compared to the SGD optimizer's sub-80% accuracy. This suggests that the NN model may be used to make accurate predictions of academic success in education [44]. Considers live online classroom dialogues analysed through natural language processing, focusing on kinds of interaction and emotional expression. It is attempting to predict the success of students in both STEM and non-STEM courses. It showed that students who achieved higher marks had emotions that are more positive

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and tended to have off-topic conversations. The study makes emphasis on the relevance of metacognitive discourse in non-STEM courses, but it finds a different emotional pattern in STEM courses. The Summary of Studies on Predicting and Improving Student Academic Performance Using DL Techniques are manifested in Table 2.

[45] proposed hybrid 2D CNN outperforms existing learning machine methods, such as k-nearest neighbour and logistic regression, in the assessment of academic success. This converts 1D data into picture data in order to study the performance of the proposed model. [46] Proposed Multi-Source Sparse Attention CNN for Course Grade Prediction. MsaCNN aggregates structured features, detects course correlations, and incorporates multi-source features to enhance the prediction. It is better than previous approaches and interpretable by a course correlation map[47]. [48] predicted student performance using DL without class imbalance. It uses a big dataset from the University of Jordan and applies oversampling and under sampling algorithms to predict student excellence particularly with the mean metric. [49] suggested two approaches to image recognition, one-channel and three-channel learning. The methods outperform machine learning algorithms like SVM and random forests in the detection of at-risk students with a high recall rate. [50] rely on K-means clustering, discriminant analysis, and CNNs in predicting academic success.

[51] presents a CNN-based approach towards enhancing classroom teaching strategies. Deep convolution networks (DCNs) are used to find the face landmarks along with optical-flow features extracted. Its purpose is to enhance the teaching effectiveness by identifying micro expressions of students. [52] discussed CNN-based architectures for the prediction of academic achievement.[53] developed CFCRS model Using Convolutional Networks for Predict Student Performance. A GCN-based model is constructed for forecasting the success of students enrolled in a Chinese-foreign cooperative higher education Program. The model has average accuracy of 81.5% in predicting at-risk pupils and outperformed SVM and random forest models. [54] proposes a methodology that combines psychometric interpretation with DL in order to predict learning performance. It presents two- and three-channel learning diagnosis methods with high prediction accuracy and interpretability, thus being able to influence personalized learning tactics. [55] discuss the prediction of student success using ANN. In doing this, the review gives weight to the need for practical implementation of ANN models in real educational environments as well as the difficulty of making the theoretically discovered results become an issue of real student outcomes gain. [56-57] suggested a method for selecting the most suitable inclusive teaching program in Peruvian higher education, addressing the needs of vulnerable groups. Using a hybrid Plithogenic AHP technique, five dimensions of inclusive education are evaluated to aid decision-making in complex educational contexts. [58] combines SWOT analysis with Neutrosophic Cognitive Maps (NCM) to evaluate strategy interconnections for developing organic farming in Tamil Nadu, India. The proposed SWOT–NCM model identifies Minimum Support Price (MSP) and centralized procurement as the most impactful strategies, offering insights for broader MCDM applications.

Table 2: Summary of Studies on Predicting and Improving Student Academic Performance Using DL Techniques

Author(s)	Technique Used	Dataset Used	Performance Score	Research Aim	Limitations
Yang & Li, 2018	SAM; BP-NN	Real academic performance data from 60 high school students	Not specified	Estimate student performance and progress using prior data	No specific performance metrics provided
Zhang et al. 2020	Correlation analysis of Moodle activity logs	Moodle LMS logs from 124 students	Correlation found between log frequency and performance	Predict students' success using LMS data and improve learning outcomes	Performance metrics are limited to correlation analysis, no accuracy metrics provided

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Hamoud et al. 2018	Decision Tree Algorithms: J48, RF, REPTree	161 student questionnaires (60 questions) covering various student life factors	J48: Best performance, though no explicit metrics	Suggest decision tree-based models for improving student performance	Limited by questionnaire design, no model evaluation metrics beyond decision tree performance
Waheed et al. 2020	Deep ANN; Clickstream data analysis from virtual learning environments	Clickstream data from virtual learning environments	Classification accuracy: 84%-93%	Predict at-risk students for early intervention	Limited to virtual learning environments and may not generalize across other systems
Hasan et al. 2020	RF, CN2 Rule Inducer, PCA	Data from learning management systems and mobile apps	RF: 88.3% accuracy	Predict student performance using video-based learning analytics	No explanation of detailed metrics or cross-validation techniques
Ani & Khor, 2024	Linear Regression, Logistic Regression, RF, KNN	MOOC dataset (demographics, academic background, course interactions)	Over 77% accuracy	Predict student performance in MOOCs based on various data features	Lack of specifics on individual model evaluation beyond accuracy
Miguéis et al. 2018	RF, DT, SVM, Naive Bayes, Bagged Trees, Boosted Trees	Data from 2459 students across 2003-2015	Above 95% accuracy	Early prediction of student academic success	Model's efficacy on different student populations or institutions is unclear
Lau et al. 2019	NN with Levenberg–Marquardt algorithm; Conventional statistical analysis	Data with 11 input variables (academic performance)	Accuracy: 84.8%	Model students' performance with NN approach	Limited to 11 input variables, model complexity and interpretability not discussed
Francis & Babu, 2019	Hybrid algorithm combining clustering and classification techniques.	Student dataset from Kerala, India	Accuracy not stated	To develop a prediction model for academic performance	Lack of specific accuracy scores or comparison with other models
Li & Liu, 2021	DNN with multiple updated hidden layers using feed-forward and backpropagation methods.	Not specified	MAE: 0.593, RMSE: 0.785	Predict academic performance and provide support for students	Limited scope on course selection and external factors not considered

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Aslam et al. 2021	DL model with SMOTE for handling imbalance; precision, recall, F-score, and accuracy for evaluation.	Mathematics and Portuguese course data	Accuracy: Portuguese: 0.964, Mathematics: 0.932	To predict academic performance early on for Portuguese & mathematics courses	An imbalance in data set could affect generalization
Nabil et al. 2021	DNN compared with DT, RF, gradient boosting, logistic regression, and others.	Dataset from a 4-year university	Accuracy: 89%	To predict students at risk of failure using DL techniques	Performance might vary with other types of courses not included in study
Yousafzai et al. 2021	Attention-based BiLSTM network	Historical student data	Accuracy: 90.16%	To predict performance based on historical academic data	May not generalize well to datasets with significantly different characteristics
Tsiakmaki et al. 2020	Transfer learning using DNNs for student performance prediction.	Student data from five compulsory courses	Not stated	Investigating the effectiveness of transfer learning in academic performance prediction	Relies on the availability of data from related courses, limited to specific cases
Semerci & Goularas, 2021	A method based on flow theory, activity heatmaps, and DNNs combined with statistical analysis.	E-learning platform interaction data	Not stated	To analyze and predict students' engagement and performance based on interaction data	Dependent on the availability of sufficient interaction data and may not apply universally
Kuo et al. 2021	Ensemble predictor using K-Means clustering and Denoising Auto-encoder with online learning for accuracy improvement.	Student data from universities in Taiwan	Not stated	Reduce resource waste by predicting student performance and providing guidance	Relies on previous course data and may be inaccurate for new students

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Abubakar i & Suprapto, 2021	NN with Adam optimization technique for better accuracy.	131 students, 22 attributes	SGD optimizer accuracy: < 80%, Adam optimizer accuracy: >96%	To predict academic performance using NNs	Low accuracy with SGD, which may affect consistency
Zhen et al. 2023	NN models analyzing classroom dialogue features using natural language processing and interpretable AI.	Classroom dialogue data from large online platform	Not stated	Analyzing the role of classroom dialogues in academic performance	Limited by data availability and focus on emotional/interaction aspects only
Poudyal et al. 2022	Hybrid 2D CNN	Academic data of students	Outperformed baseline models (k-NN, Naive Bayes, etc.)	To enhance the prediction of students' education performance by hybrid CNN	Limited by the 1D to 2D data transformation
Zhang et al. 2021	Multi-source sparse attention CNN (MsaCNN)	Real-world university dataset	Better performance than traditional methods	Predict academic performance by capturing course relationships	Lack of real-time prediction validation
Alshamaila et al. 2024	DL with oversampling/undersampling methods	University dataset (University of Jordan)	High mean	Address class imbalance and predict student performance	Limited exploration of other imbalance techniques
Yang et al. 2020	One-channel and three-channel image recognition	5235 students, 576 absolute/1728 relative input variables	Average recall rate: 77.26%	Early identification of at-risk students	Limited to mid-semester prediction, no longitudinal study
Feng et al. 2022	Clustering, discrimination, and CNN	Academic data	Effective prediction results	Integrate multiple techniques to predict student outcomes	Limited scope to clustering and K-means optimization
Pei & Shan, 2019	Multi-task deep CNN for micro-expression recognition	Classroom facial expressions	High accuracy	Monitor and enhance classroom teaching effectiveness	Focused on facial recognition and micro-expressions only

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Alshaikh & Hewahi, 2024	DL (CNN)	Public datasets	Not mentioned	Investigate effectiveness of DL for student prediction	Dataset limitations and class imbalance addressed
Hai-tao et al. 2021	Graph convolutional network	CFCRS student data	81.5% accuracy	Predict performance of students in Chinese-foreign cooperation schools	Limited to CFCRS context, not generalizable
Wang et al. 2023	Unified interpretable intelligent learning diagnosis framework	Two real-world datasets	Higher accuracy than state-of-the-art models	Provide interpretability for learning diagnosis	High computational complexity, and interpretability challenges
Baashar et al. 2022	ANN	Various datasets in higher education	No specific performance score provided	Survey existing literature on ANN applications in education	Limited real-life application of ANN in improving performance

5. Chronological Review

Over the last few decades, there has been a tremendous amount of advancement in student performance prediction through systematic methods. During the early 2000s, most of the field was engaged with traditional statistical approaches such as linear regression and decision trees. These methodologies formed a framework for assessing student behaviour's and academic patterns but had limitations in terms of scalability and accuracy. By the mid-2010s, the integration of machine learning methods like SVM and ensemble models has led to a significant increase in prediction skills. This period also introduced educational data mining technologies that enhanced the management of organized and unstructured educational datasets. The DL models, including NNs, CNNs, and RNNs, first came in the late 2010s and beyond and transformed the way student performance prediction works. These models were highly performing at handling complex, high-dimensional data, providing insights about the learning habits of the student. Recent advances in such areas as hybrid DL models and real-time analytics systems have closed the main gaps in scalability and model interpretability. However, other challenges like data heterogeneity, ethical issues, and openness still exist, making it an open door to study further for developing predictive frameworks in even more inclusive and effective educational systems.

6. Result analysis

The commonly used databases and the commonly measured performance metrics used in the existing studies were discussed in this section.

A. Metrics analysis

The commonly used metrics such as accuracy, RMSE, and MAE were analyzed from the existing studies.

- **Accuracy**

The Figure 14 shows the accuracy for several writers' theories and approaches applied for forecasting student achievement. A considerable variation in accuracy could be seen among methodologies, datasets, and evaluation measures. Among the top-performing studies, [16], [17] achieved accuracies of 99.5% and 99.4%, respectively. These results prove the potential of DL and advanced ML approaches for near-perfect prediction. However, works like [15] and [24] showed lesser accuracies at 60% and 74%, respectively, that might be due to issues like smaller datasets, feature engineering difficulties, or model complexity.

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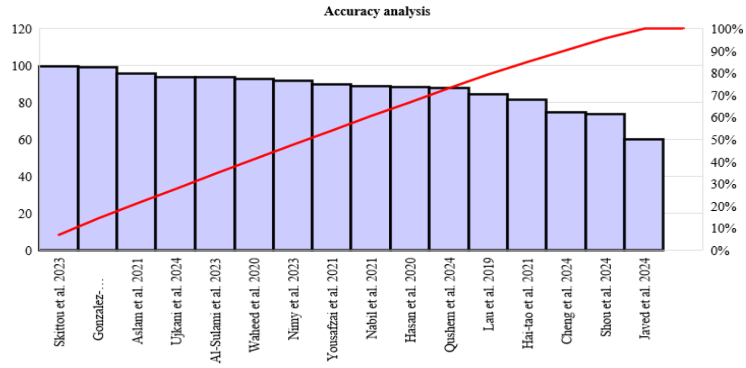

Figure 7. Accuracy comparison

Moderate performance is shown by studies like [57] 78%, [35] 84.8%, and [53] 81.5%. Numbers indicate that scope is open for improvement through sophisticated model usage and fine-tuning data preprocessing. The overall trend in the performance of models reveals that it has improved with time, and research that is more recent shows higher accuracy resulting from better methodologies, higher availability of datasets, and more advanced model architectures. Yet, there is a great need for further research to standardize the evaluation methodologies as well as overcome important gaps in low-performing models.

- **RMSE analysis**

The Figure 15 below summarizes the RMSE values published by several authors to show the variable levels of model performance. Lower values of RMSE imply that the predicted accuracy is better, and in this regard, [37] earned the best result with an RMSE of 0.785, meaning that their model is highly precise.

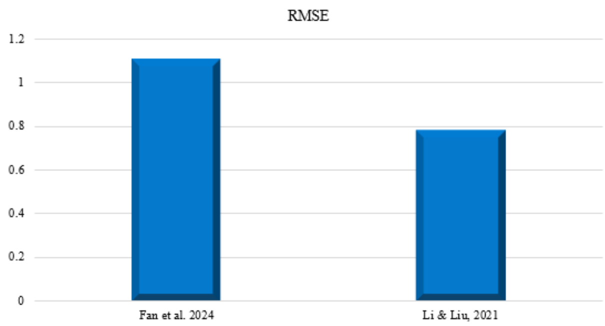

Figure 8. RMSE analysis

[23] presented a little higher value of RMSE, such as 1.1099 and 1.13, respectively, thus indicating strong predictive ability, but still with room for small improvements.

- **MAE analysis**

The MAE results show significant variation in the accuracy predicted by both models has been given in Figure 16. [37] had an exceptionally low MAE of 0.593, which suggests that predictions were very accurate in the study.

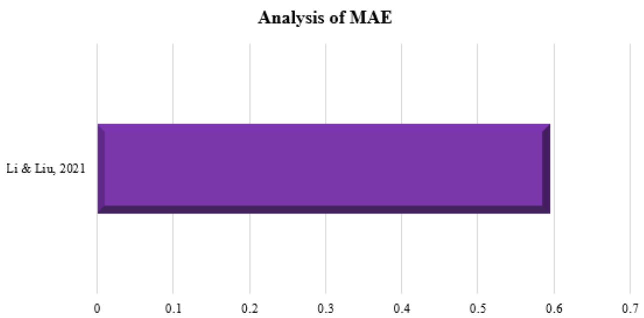

Figure 9. MAE comparison

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B. Database comparison

The studies analyzed employ various datasets in examining predictive models of student performance. Examples are those from [6], which relied on data coming from Moodle, demographics information, and performance records, and others by [7] relying on district data from a school system. [8] and [24] made use of the OULAD and noted this one to be useful broadly. [13] conducted research on the activity of LMS at King Abdulaziz University, while [17] considered the performance of 14,495 undergraduate students.[15] considered data from online university learning and [19] has considered MOOC learner's data. Other studies include the works of [14] using open VLE datasets and performance of students as considered in the study of [23]. These various databases thus emphasize the value of institutional, demographic, and learning activity data for better predictive models.

[27] employed actual academic performance data from 60 high school students. [29] employed Moodle LMS logs from 124 students. [30] used student questionnaires from 161 individuals. Data clickstream from virtual learning. [32] incorporated data from learning management system and mobile applications. Dataset was used by [33] from MOOCs. Miguéis et al. (2018) dealt with data of 2459 students from 2003 through 2015. [35] analyzed the academic data with 11 input variables. [36] used the student database of Kerala, India [37] worked on data related to course selection. [40] analysed the data of five compulsory courses. [41] analyzed the data of interactions in an e-learning platform. [42] utilized the students' data of Taiwan universities. [43] analyzed the academic performance data of 131 students. [44] Extracted the characteristics of classroom discourse from academic data. [45] explored academic data for performance prediction. [46] analyzed a real-world university dataset. [48] utilized data from the University of Jordan. [49] utilized data from 5235 students. [50] utilized academic data to cluster and discriminate. [51] utilized classroom facial expression data for recognition. [52] made use of publicly available datasets for the prediction of student achievement. [53] made use of data obtained from students in CFCRS. [55] worked with various datasets for the deployment of ANNs.

7. Research gap

The study of performance prediction and learning systems on students has advanced significantly, and yet there are still certain holes that must be filled in. Models' generalizability on varied educational environments is of significant need. Many research works are limited to certain institutes, datasets, or locales, which limits the generalizability of their findings. For instance, models constructed using data from a single university or course often fail to perform well in other contexts, such as rural or foreign settings. The lack of uniform datasets and standardized evaluation techniques exacerbates the problem, making it difficult to develop generally applicable forecasting tools. Another significant gap is the integration of numerous data sources and prediction methods. While many studies use ML & DL algorithms, the conspicuous lack of research integrates these techniques with psychological or behavioural data to provide a better picture of student performance. Further, research is sometimes limited to only one paradigm, be it DL or decision trees, without considering the benefits that hybrid or ensemble models could bring to improve accuracy. The focus is on academic success, and in most instances, other parameters such as emotional, psychological, and socioeconomic characteristics may influence a student's achievement are left unexplored.

Lastly, more research work is necessary on the use of the predictive models in school settings as well as on their in-situ deployment. Much of the available research focuses on theoretical models or datasets that do not reflect accurately the complexities in real education settings. Moreover, though some researchers have promoted early intervention strategies or customized learning resources, their effectiveness in the real classroom environment is often not tested. Further research on the scalability, accessibility, and user acceptance of these models is important to their wider use in a variety of educational situations.

8. Conclusion

Finally, the study underlines the importance of predictive models and DL techniques in forecasting student performance and educational outcomes. The study calls for the integration of multiple data sources such as academic records, behavioural patterns, and socio-emotional aspects by investigating approaches such as decision trees, DL and hybrid models. Despite the promising results, the study mentions a few key hurdles: namely, that more generalized models are needed, the inclusion of psychological elements, and the applicability of the systems in real-world scenarios. This will be critical in creating more accurate, efficient, and personalized instructional tools that can be used efficiently in a variety of educational settings.

9. Future scope

Future work could focus on expanding the datasets used to create more generalized and diversified predictive models for student performance. Adding real-time data from learning management systems and behavioural analytics may improve the accuracy of predictions. Additionally, studying the inclusion of psychological factors and emotional intelligence in prediction models may provide richer insights into student achievement. Real-world testing and validation of these models by collaborating with educational institutions will be beneficial in their fine-

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tuning. Moreover, study on the usage of explainable AI techniques can also make the forecast more transparent and interpretable for educators and administrators.

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