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Review Article

Closing the gap: exploring the untapped potential of machine learning in deaf students and hearing students' academic performance

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Abstract
Assessments and critical feedback play a crucial role in helping students not only master a skill but also apply it effectively. Educational data mining (EDM) and machine learning (ML) tools are aiding educators in tailoring teaching strategies to individual student needs. While predictive analytics are widely used for hearing students, there is a notable gap in research on deaf students. Assessing deaf students necessitates the expertise of trained specialists, and their feedback is particularly critical in assisting these students in skill mastery. Various strategies have been developed to analyze the academic performance of deaf children, but there is a lack of integration of data to create a model categorizing different methods of early classification based on student academic performance. As part of a broader effort to address challenges faced by students struggling with speech perception and language development, there is an opportunity to conduct a systematic study of early academic interventions for deaf students. Failure to address these issues can result in an increased risk of delays in social-emotional development. The findings from our review highlight several key aspects, including (i) ML and EDM-based applications for student performance analysis, (ii) factors influencing academic performance among deaf students, (iii) potential EDM methods useful for assessing deaf children, (iv) the absence of benchmark data and the need for interpretability in existing methods, (v) the necessity for ML approaches in predicting the performance of deaf students, and (vi) the anticipated major assessment trend in the future through deep learning models. Our findings have implications for various stakeholders in education, including teachers, students, administrators, and researchers.

Keywords
Machine learning, Deaf education, Academic performance analysis, Educational data mining.

1.Introduction
Modern universities use several methods to improve the learning environment. This includes analyzing the academic performance of students and planning various intervention programs to support the students to overcome the difficulties they face. The performance prediction at the time of admission and in the subsequent years helps universities effectively plan the intervention strategies which in turn can help both management and educators benefit from the students' performance prediction plans [1]. Educational data mining (EDM) and machine learning (ML) methods are gaining popularity in the educational domain. Many applications using these techniques are used to analyse student performance in academics.

The EDM and ML-based applications help instructors to identify struggling students earlier and take action to improve success and retention. Researchers are using these techniques to accelerate their research to uncover discoveries and insights. Though the role of ML and EDM is explored considerably in the education of hearing students, its benefits are not used properly in deaf education. Research suggests that deaf young adults are less likely than their hearing peers to live independently[2], are underemployed and underpaid [3], and are less likely to obtain an undergraduate-level degree [4]. The opportunities for higher

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education are limited to deaf students and the features that affect their performance are yet to explore. The application of EDM and ML techniques can be used to analyze data generated in the deaf education domain and can be used to improve the academic conditions of deaf scholars.

Though ML and EDM-based applications are transforming the education domain, there is no comprehensive organization of findings of various studies for the different stakeholders of deaf education which may in turn be useful for the identification of research gaps and further research in this area. Here the attempt is to review the literature to identify the recent developments in this area by considering the research works during the period 2017 to 2023.

This paper is organized as follows: the first section presents the background to the role of ML and DM in education, in general, and deaf education, in specific. The following sections include the methodology followed, the results, its critical analysis of results and conclusion and future scope of this study.

1.1Background

A number of benefits come from using ML models to predict academic achievement, including potential for research, efficiency, scalability, early warning systems, predictive insights, and personalised instruction. Teachers may use these models to customise their instruction for each student, recognise at-risk pupils early, find hidden trends in student data, save time and money, adjust and get better over time, and support education-related research. These advantages have the capacity to expedite instructional procedures while boosting student achievement and raising educational standards. Feature selection, unbalanced data, managing temporal elements, data privacy and ethics, data quality and quantity, and model interpretability are some of the challenges associated with using ML models to predict academic success. These issues include the requirement for trustworthy diverse data, ethical utilisation of student data, the selection of appropriate predictors, the management of temporal dependencies, the correction of unbalanced class distributions, and the clear explanation of model findings. Though there are many challenges in general education domain for developing applications using ML techniques, when deaf education domain is considered, the challenges are much greater. So, these challenges are considered separately in section 1.1.2.

1.1.1 ML and educational datamining in education

In 2008, during International Conference on EDM and the Journal of EDM has evolved as a trustworthy area of research [5]. The International EDM Society,2011 states that as the amount of data generated in educational domain is large, EDM as an emerging discipline can be used to develop methods to explore this data and to understand the student needs and the setting in which they learn. Educators, academics responsible administrators or policymakers, and students are considered the major stakeholders of education. The extensive review considers the major research conducted on EDM during the period 1995 to 2005 and shows that the development of EDM considers the needs of all stakeholders through the objectives of the different stakeholders are different [6]. To optimize traditional education, an interdisciplinary approach to education is required to develop personalized, adaptive, and effective learning environments. Artificial intelligence, which can be considered a superset of ML, has a significant role in achieving long-term change at all levels of the education system, including educational institution administration and management[7]. The educators mainly focus on the improvement of the learning of students. Considering the individual differences in students, the customized plan of teaching gives better student performance. The educators can obtain the required information using EDM to make individualized teaching plans for students. It enables educators to categorise students according to their needs or performance, investigate their learning behaviour, and redesign the course to meet the needs of the students. The EDM provides adequate insights to administrators which will help them to find appropriate parameters that will help in the overall effectiveness of the organization. The student gets valuable feedback about his performance which may help him with self-analysis and find ways to improve his performance. The role of EDM in decision-making helps the government and policymakers in making effective decisions [8].

The applications of ML methods to predict students' performance-based socio-economic factors and assessments are useful in foreseeing success. Different ML algorithms listed below were found to be effective for the purpose [5]. Effective decisions can be made based on the information obtained from different algorithms of learning and predictive analytics. These algorithms can be used in the educational domain to analyse educational data, identify the issues faced and recommend effective solutions. The prediction algorithms are used to predict the performance of students in academics [9], the student attrition after the course enrolment [10], and select a suitable study track for a student [11]. According to the behaviour of students, they can be grouped using clustering techniques. This algorithm can be to identify active students from non-active students based on their participation and performance in activities [12], group the students according to behavioural and personality factors that influence their academic performance[13], and students can also be grouped according to their academic performance[14]. The models designed based on the algorithms can be used for the plan intervention strategies that helps at risk students [15], predict student grade point average[16], and predict performance in online learning[17]. Generally, ML models used in this domain use clustering, classification, and prediction techniques. Relationship mining [12] is another application that uses association rules in mining to find good relationships between items in a given dataset. The underlying correlations among courses need to be identified properly to predict the performance of the student accurately [18].

1.1.2 Challenges in deaf education

According to the report from World Health Organisation (WHO), currently 15% of the overall population is people with disability, with nearly 450 million individuals suffering from hearing loss. It is estimated that by 2050, there would be more than 900 million people [19]. Different government agencies made rules which assure to provide, promote and ensure that people with disabilities have equal access to adult education and continuing education programmes as others. As education plays a vital role in the quality of living, the factors affecting the education of this population need to be studied. In formulation of policies, this can be helpful for government and other stakeholders of education [20].

Hearing is an important gateway to learning. In school environment, all the formal learning and educational activities are facilitated through the sense of hearing, so any hearing loss without providing learning accommodations compromises effective learning [21]. The major challenge faced by a deaf student is the communication barrier. It affects his academics considerably. Though no significant data is available from measuring the literacy skills of deaf students, informal observations show that deaf students take many years to attain required literacy skills and sometimes they do not attain that level too. [22]. Various factors have had an impact on the poor academic performance of deaf students. Poor academic achievement has resulted in low employability, low income, and poor quality of life. As a result, studies into the performance of deaf students and the factors that influence it must be thoroughly examined. Despite all of the anticipated breakthroughs in deaf education, deaf children continue to fall academically behind their hearing peers. Many of them do not acquire the necessary knowledge and skills to fully realise their potential [23]. Teachers and other service providers find it challenging to employ appropriate pedagogies in the classroom [24].

1.2Motivation and objectives

The involvement of a special educator plays a pivotal role in the educational journey of a deaf student. However, it's crucial to recognize that each deaf student's academic needs are influenced by various factors such as the learning environment, characteristics related to deafness, economic circumstances, behavior, and language skills, all of which can vary significantly from one student to another. To address these unique needs effectively, the integration of technology-assisted student grouping can be a promising approach, allowing for the creation of tailored lesson plans for each individual deaf student. Additionally, the identification of their specific learning styles is instrumental in designing instructions that align with the curriculum delivery. This review paper aims to shed light on the importance of research in the field of deaf education, particularly within the context of general education, utilizing ML techniques. The primary objectives of this study are as follows:

- Comprehensive Literature Analysis: To provide an in-depth analysis of significant research efforts in the realm of deaf education and general education that have incorporated ML approaches. By doing so, we aim to consolidate the existing knowledge in this domain.
- Identifying Research Gaps: To pinpoint the existing gaps in the current body of research related to ML applications in deaf education and general education. This identification of gaps will serve as a foundation for future research initiatives.
- Promoting Further Research: To encourage and guide future research studies by highlighting the areas within deaf education and general education where additional investigations are needed. By identifying these gaps, we aim to inspire researchers to explore uncharted territories and contribute to the advancement of educational conditions for deaf students.

2.Method

The preferred reporting items for systematic reviews and meta-analyses, PRISMA, suggests a systematic way of conducting a standalone literature and it is followed in this paper. There are other methods followed in many other reviews[25–28] but the PRISMA guidelines provide a consolidated step by step process of conducting a literature review which is concise and complete. The *Figure 1* gives the step by step process according to PRISMA guidelines.

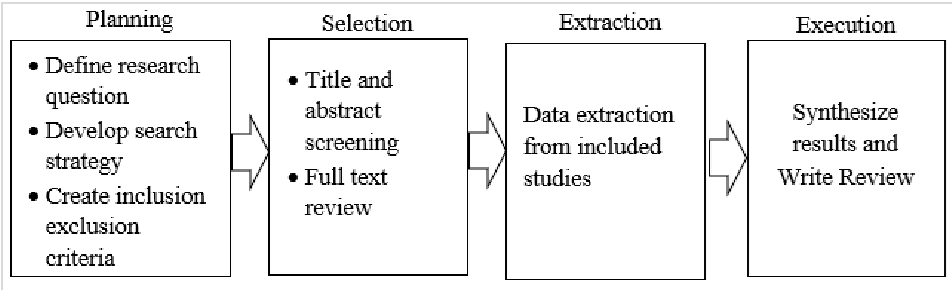

Figure 1 PRISMA model for systematic literature review

The following thoughts helped the authors of this paper to formulate the research questions (RQs).

1. What are the applications of ML and EDM in education domain
2. Is there any specific factors that affect the academic performance of students with hearing impairment
3. To what extend the ML models are helpful in solving problems faced in educational domain
4. Are the models used in these studies explainable

Based on the above thoughts the RQS are formulated.

2.1Planning

The planning phase include

- Defining RQs
- Identifying relevant terms for searching
- Developing search plan

2.1.1Research questions

The major findings of the review are structured based on the following three RQs:

RQ1.What ML and EDM-based applications are being used in student performance analysis?

RQ2.What features and datasets are used for performance analysis of students in general and deaf students in specific?

RQ3. What are the advantages of using explainable models in this domain?

2.1.2Search terms

- ML AND student performance OR EDM AND student performance
- Academic performance AND Deaf
- ML AND students with Hearing Impairment OR EDM AND students with Hearing Impairment
- AND student performance prediction
- Open Dataset AND student performance

2.1.3Search plan

The authors decided to collect the papers independently and to select the papers based on inclusion exclusion criteria collectively. The inclusion -exclusion criteria is represented in *Table 1.*

2.2Selection

The PRISMA model for systematic literature review is used for paper selection. Considering the inclusion-exclusion criteria, the authors collected papers independently. The diagrammatic representation of procedure followed in line with PRISMA model is given in *Figure 2.*

2.3Extraction

To find the primary data and for the relevant papers five databases are used mainly. They are Google scholar, research gate, IEEE Xplore digital access library, Springer, Scopus and directory of open access journals. The free reference management application Mendeley is used to store, organize and search the references from just one library. To review the recent developments in this domain the duration of publications to be considered was fixed as last seven years including the year of study. The papers from the year 2017 to 2023 are used for this study as per the inclusion criteria and all the 81 papers in the bibliography are included in this paper. The *Figure 3* show the count of works included in this paper for each year.

2.4Quality assessment criteria

The following are set as quality assessment criteria (QAC) for the review.

QAC1: Clearly defined objectives of the review

QAC2: Analysis of RQs based on existing methods

QAC3: Proper identification of research gaps
QAC4: Relevance and recency of Sources
QAC5: Source credibility
QAC6: Reproducibility and generalizability

Table 1 Inclusion exclusion criteria

Criterion	Inclusion criteria	Exclusion criteria
Publication year	Papers published during 2017 -2023	Papers published before 2017
Relevance	Papers directly related to academic performance prediction using ML	Papers not related to research topic
Data Quality	Papers with good quality data and data sources	Papers poorly documented
Research Method	Papers with strong research methods, suitable data analysis strategies, and understandable explanations	Publications that lack methodological clarity, adequate analysis, or both
Language	Papers that use English language	Papers in language other than English
Peer reviewed	Papers that are published in a blind reviewed journal	Newspaper articles, Wikipedia articles, blogs, Short papers, Editorials and patents
Publication Source	Publications from reputable conferences, journals, or organisations	Publications from unknown or unreliable sources

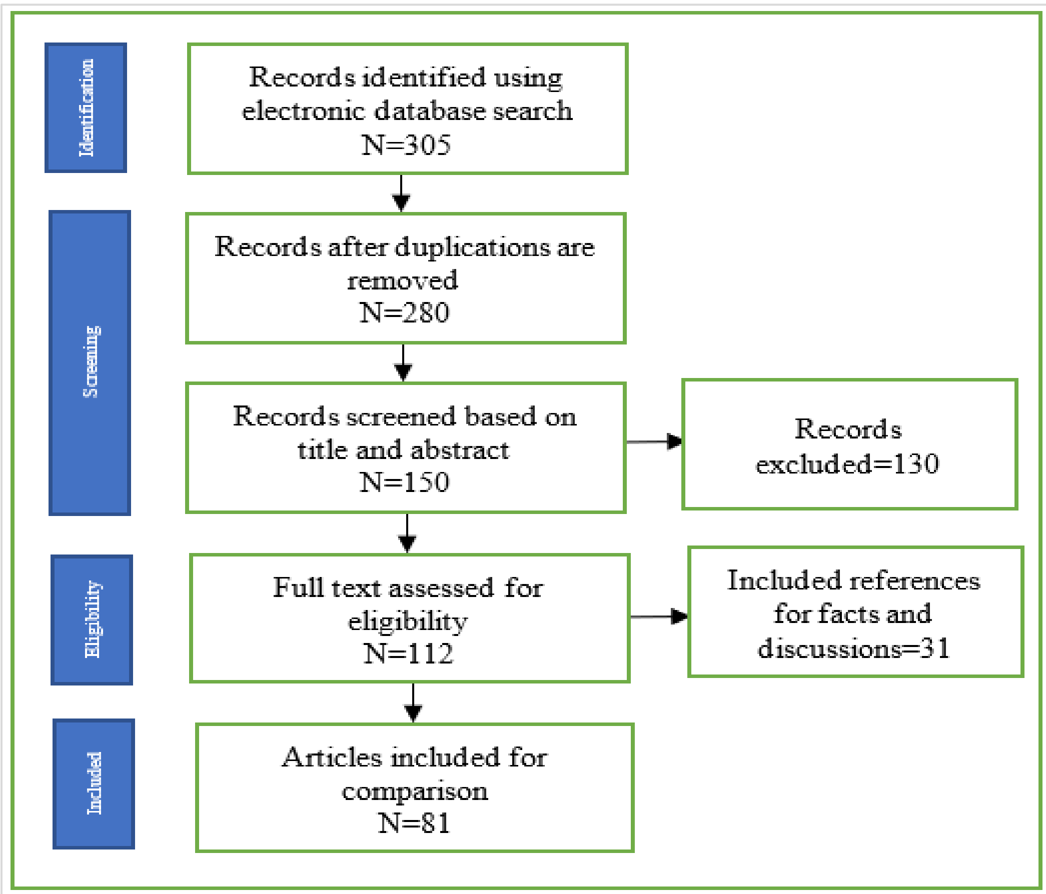

Figure 2 PRISMA diagram for article screening

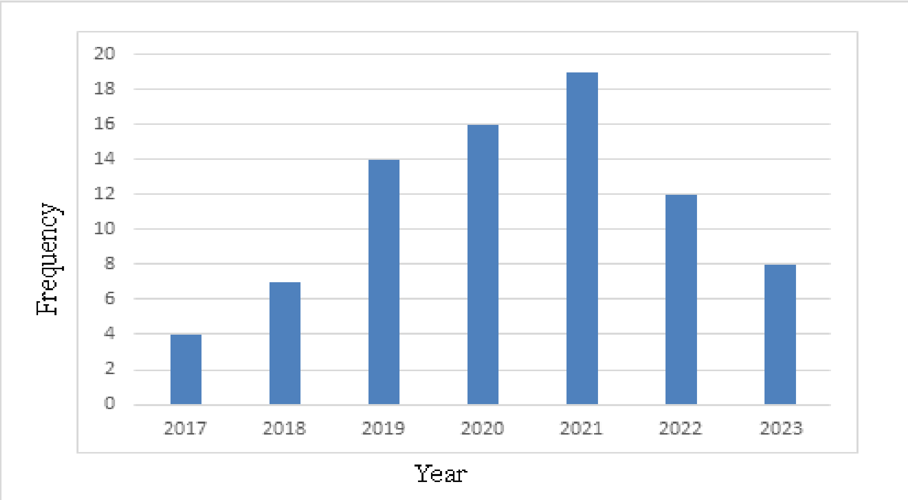

Figure 3 Year-wise distributions of studies under review

3.Results and discussions

The expansion of abbreviations is given in *Appendix I*. The studies under review are critically analysed and tabulated added to the *Appendix II*. Out of the papers reviewed, the significant research works in the recent years, 2021-2023, is analysed in *Table 2*. The following section consists of the detailed analysis performed based on the RQs

Table 2 Analysis of significant research works in the years-2021,2022 and 2023

Paper	Approach	Advantages	Limitations	Results
[29]	Mark and grade prediction	Improved accuracy, Specific grouping, Knowledge area analysis, GA-based decision tree(DT), Regression	Grouping complexity, Subject variation, Data volume	96.64% classification accuracy, RMSE: 5.34, Effective academic performance prediction, Future deep learning integration
[30]	Predict student performance using ML, analyze past results, talents, interests.	Tailor instruction, evaluate teacher effectiveness, improve education quality, assess question paper difficulty.	Data quality, result interpretation, resource-intensive, performance variation, historical data dependency.	Best Performance - support vector machine (SVM)
[31]	Dropout prediction, factorization machine, feature engineering	Captures complex relationships, interprets dropout reasons, provides actionable insights.	model interpretability, data dependency.	DeepFM: 99% accuracy on validation data, outperforms other methods.
[32]	Transformer encoder model to predict at-risk students based on LMS interactions.	76% accuracy in predicting at-risk students at 20% course completion, with 83% accuracy for the W-PD task.	Positional encoding led to performance degradation due to feature value changes, but feature aggregation had minimal effect.	Transformer encoder performed better, with 1% to 3% higher accuracy and 3% to 7% higher F1-score compared to long short-term memory (LSTM)
[33]	Data mining analysis of student performance's impact on grade point average (GPA), using clustering and classification techniques.	Enhanced understanding, predictive capabilities, early-stage risk mitigation for educational systems.	Interpretability challenges, reliance on available features and metrics	Identification of relationships between admission scores, courses, achievement tests, and GPA. Evaluation of ML models for early-stage

Paper	Approach	Advantages	Limitations	Results
				performance prediction
[34]	Hybrid ensemble model with supervised ML algorithms to predict students at risk.	Early identification of at-risk students, improved performance with Stratified K-Fold Cross Validation and hyperparameter optimization.	Consideration of Turkey-specific education system features, varying performance with different meta learners in the hybrid model.	Best accuracy achieved by Logistic Regression(LR) (94.4%). Hybrid model with SVM meta learner reaches 94.8% accuracy and 96.8% precision.
[35]	Student performance prediction framework with PCA for feature handling, recurrent neural network encoding, and attention mechanism.	Enhanced student performance prediction accuracy, personalized learning recommendations, in-depth analysis of knowledge states, and feature importance prioritization.	Does not consider the impact of knowledge concept relations on student performance prediction.	Proposed Framework outperforms other methods, providing more accurate predictions and personalized learning program recommendations.
[36]	Investigate the influence of parental involvement on the academic performance of learners with hearing impairment in Kogi state.	Use of a descriptive research design allows for a detailed exploration of the relationship and the purposive random sampling technique enhances the relevance of the sample.	The study focuses on a specific region, which may limit the generalizability of the findings The sample size of 100 parents may be considered relatively small.	Highlights the significant role of parental involvement as a potent tool that can either positively or negatively impact the academic performance of learners with hearing impairment.
[37]	Introduces a ML based model predicting undergraduate students' final exam grades, leveraging midterm exam scores as input data.	Leverage s ML algorithms to predict final exam grades, providing a proactive approach to identifying potential academic outcomes.	The dataset is limited to students of a specific course in a particular university during a specific semester, potentially limiting the generalizability of the findings.	Establishes a learning analysis framework in higher education and aiding decision-making processes. It identifies ML algorithms that perform more accurately in predicting academic achievement grades.
[38]	Use intelligent techniques and algorithms to analyze student data and generate insights into student performance.	The framework integrates regression and classification models to analyze factors affecting student performance and introduces an interpretable framework for insights from e-learning platform data using ML algorithms.	While the framework is described as interpretable, the actual interpretability of the ML models may vary, and this potential trade-off is not explicitly discussed.	Emphasizing model diversity, precision, and predictive modeling enhances practical applications for identifying and supporting at-risk students. Study results indicate the proposed framework is accurate and valuable for educational decision-making
[39]	Introduces a step-wise interpretability model and extends the Local interpretable model agnostic explanations (LIME) method to enhance the understanding of important features, counterfactuals, and causal relations for personalized intervention systems.	Multidisciplinary approach which uses step wise model with minimal counterfactual LIME for theoretical and causal reasoning for the deeper understanding of relations in student success prediction	Emphasizes the need of adjustments in a different setting. Absence of actual application in real life setting.	Study successfully recover connections among features using artificial data.

Paper	Approach	Advantages	Limitations	Results
[40]	Predicting at risk students using classification models, identifying most influential factors using feature selection methods, addresses imbalance issues and using interpretability methods to explain student failure.	Diverse algorithmic approach, feature selection optimization, imbalance balancing, performance benchmarking and explanation with explainable artificial intelligence (XAI) techniques.	Dataset specificity, generalising issues and real time application using XAI.	The models' dependability and interpretability are improved by the multifaceted approach that combines algorithmic selection, feature optimisation, and explanation using XAI approaches. This offers insightful information to educators and educational institutions.
[41]	Four-step LR procedure to analyze data collected from 1723 student-teachers to understand the complex issue of student-teacher dropout.	Holistic approach to the variables-personal, socioeconomic and academic-to understand the variables affecting student-teacher drop out.	Limited generalizability, factors like socio political and mental issues can also be considered.	Insights into the multifaceted issue of student-teacher dropout, offering a basis for informed interventions and policies in least-developed countries and potentially inspiring further research in diverse educational settings.
[42]	Uses a Catboost–SHAP-based academic achievement prediction algorithm and a K-prototype-based student portrait creation to provide interpretability and transparency while addressing probable academic issues in a holistic manner.	The suggested approach outperforms existing algorithms in terms of early academic crisis identification and decision-supporting visual analysis.	The study's focus on a particular university restricts generalizability, desensitisation of multi-source student data may affect model sensitivity, and the current exclusion of time-series data may impede a thorough grasp of academic dynamics.	For academic performance prediction, Catboost-SHAP model perfroms better than other classical classification models allowing early detection of at-risk students nad interpretable visual analysis for efficient decision-making support.
[43]	Distinguishes nuanced emotions in MOOC discussion forum posts using an ensemble method, extracting feature categories of engagement and semantics. Employs stacked and voting methods for performance comparison in predicting student grades.	The stacked ensemble method excels in accurately predicting student grades by incorporating distinct feature categories—engagement, semantics, and sentiment. It provides a nuanced understanding of student emotions beyond traditional sentiment analysis.	Limitations of relying solely on textual data and the potential impact of other unaccounted factors on student grades may affect the overall predictive accuracy.	The stacked method outperforms alternatives in accurately predicting student grades, with the Random Forest baseline revealing that negative sentiment and stress have limited impact on academic results.
[44]	Investigates the perceptions of teachers and pupils regarding factors influencing the academic performance of learners with hearing impairment in selected schools in Zambia.	The qualitative approach and case study design, diverse perspectives by including pupils, teachers, and head teachers, contextual relevance of the findings.	Limitation in generalizability, qualitative research is inherently subjective, limited sample size.	Study recommends upgrading teachers' competence in sign language and providing an enriched learning environment, instructional resources, and support to improve

Paper	Approach	Advantages	Limitations	Results
				academic success among pupils with hearing impairment.
[45]	Develop an automated technique for predicting student performance using the attention-based Bidirectional Long Short-Term Memory (BiLSTM) network	Automatic extraction of high-level features from historical academic data, the proposed method capitalizes on the superior sequence learning capabilities of BiLSTM, practical significance offering insights to academicians, universities, and government departments.	Any limitations or biases present in the dataset may impact the model's performance, can be computationally intensive, requiring substantial computational resources	Attention-based BiLSTM model achieves a prediction accuracy of 90.16%, providing academicians and institutions with a powerful tool for early identification of academic outcomes.
[46]	Introduces a dual-input deep learning model that simultaneously processing time-series and tabular data for predicting university students' Grade Point Average.	Model's ability to handle both time-series and tabular data sets, superior capability in explaining the true distribution of students' GPA compared to alternative models.	The study identifies that multilayer perceptron- long short term memory (MLP-LSTM) performs well with a smooth target GPA distribution, which may not be prevalent in actual data.	MLP-LSTM emerges as the best-performing model, highlights challenges related to the target GPA distribution and long-range dependencies.
[47]	Analyzes academic performance using both deep learning regression and linear regression models, addressing the challenge of overfitting in smaller datasets	Uses regression models to analyze academic performance, showcasing its adaptability to diverse domains, deep learning regression model outperforms the linear regression model	Utilizes academic records of students who have completed their courses, limiting the model's predictive scope to final percentages. This restricts the application of predictions during the middle of a course.	Deep learning regression model suggests the superiority of deep learning in predicting academic performance, showcases the adaptability and scalability of the deep learning approach.
[48]	The study emphasizes the critical role of education in shaping a productive life and addresses the challenge of predicting academic performance using a hybrid approach.	Provides comprehensive decision support to students, offering insights through motivational comments and video recommendations for informed course selection, contribute to a significant reduction in dropout rates.	The study's model is presented as a prototype, and its effectiveness needs validation on a real-time large dataset, model's performance depends on data quality.	Hybrid approach, combining cluster-based linear discriminant analysis (CLDA) and artificial neural network (ANN) shows promise in guiding students towards appropriate course selections and reducing dropout rates.
[49]	Predicts students' performance in higher education using deep neural networks (DNN), aiding in course selection, study plan design, and overall academic support.	Assists in selecting courses and designing study plans, providing support to both students and educators, reduces official warnings and student expulsions by identifying inefficiencies early, allowing for timely interventions and support.	To maintain prediction accuracy, continuous updates in extracted features and their corresponding weights is needed.	The proposed DNN model proves its worth with efficient results, suggests practical applicability, aiding educational institutions in managing staff and students, reducing educational difficulties, and contributing to the development of future education policies.
[50]	Analyses a benchmark dataset of over 700k records of deaf	Insightful feature engineering, the application of time series	While the findings are significant for the	Attributes like student grades, demographics,

Paper	Approach	Advantages	Limitations	Results
	and hard-of-hearing students in Saudi general education, aiming to provide a robust model for accurately predicting the academic performance of these students.	analysis algorithms proves effective in predicting academic performance with high accuracy, Data size is considerable,	specific context of Saudi general education, generalizing the results to different educational settings may require careful consideration.	geography, school, course type, and score correlate strongly with academic outcomes for deaf and hard-of-hearing students. Religious curricula, Arabic language, and mathematics are key predictors of academic success or failure. The time series analysis algorithm is highly accurate in predicting academic performance.
[51]	Addresses the challenges of integrating digital data from various sources to provide a comprehensive view of a student, predicting academic performance, and fostering positive student engagement.	Combines multisource behavioral data providing a holistic view of students' lifestyles, employs LSTM to extract features representing dynamic changes in temporal lifestyle patterns, enhancing the model's ability to capture complex behavioral dynamics	Relevant features such as peer effects and sleep are not evaluated, limiting the comprehensiveness of the model, study sacrifices dataset scale to obtain a multisource dataset by using student-generated data within a single course	The proposed model, Augmented Education (AugmentED) leverages metrics measuring linear and nonlinear behavioral changes, along with LSTM for dynamic feature extraction, contributing to effective feature representation, designs visualized feedback to empower students to achieve better student life balance.
[52]	Uses EDM to predict students' academic performance, specifically focusing on courses like "Programming" and "Data Structures" with the goal to identify students at risk of failure and explore the efficiency of deep learning in EDM.	The DNN model demonstrates high efficiency in predicting students' performance in data structure courses and identifying at-risk students early in the semester, comparison is made between various resampling methods, such as synthetic minority oversampling technique (SMOTE), adaptive synthetic (ADASYN), Robot Operating System (ROS), and SMOTE-ENN, to address the imbalanced dataset problem.	Limitation in generalizability, addresses the imbalanced dataset problem through resampling methods	The DNN model achieves an accuracy of 89%
[53]	Addresses the urgent need for predictive analytics applications in higher education institutions, focusing on predicting final student grades in first-semester courses.	Compares the performance of six well-known ML techniques, addresses challenges related to imbalanced datasets, specifically employing SMOTE, proposed model, integrated with Random Forest, demonstrates highest f-measure of 99.5%.	Limited generalizability, proposed model integrates Random Forest for improved performance, the complexity of the model should be considered, and its applicability to different contexts may vary.	Proposes a multiclass prediction model. Utilizing SMOTE for oversampling, handles imbalanced datasets, the integration of Random Forest in the proposed model yields the highest f-measure of 99.5%.

3.1ML and EDM-based applications for student performance analysis

RQ1: How ML and EDM-based applications are being used in the student performance analysis?

There are several ML and EDM-based applications for student performance analysis that helps the different stakeholders of education. The summary of ML and EDM applications for student performance analysis is presented in *Table 3.* The basic applications that deal with academic performance can be summarized as follows.

3.1.1Performance prediction before the course commencement

The ML algorithms and techniques can be used right from the beginning of the admission of students [54] tried to predict the student performance before the commencement of the course. This study was as a multi-instance multi-label problem by considering the performance of a student in previous courses to predict the performance in new courses. The pre-admission criteria like high school grade average, scholastic achievement admission test score, and General aptitude test score were considered to predict the student's performance before admission[55]. Uses clustering and classification method for the early prediction of performance[33]. The early prediction of drop outs during the admission may help the teachers to introduce suitable pedagogy for those who needed [56, 57].

3.1.2Prediction of at-risk students

Another area that is addressed by ML is the identification of at-risk students [58, 41, 59]. The early warning systems for at-risk students [60, 61] proposed aimed to identify the at-risk students at the earliest so that intervention programs can be planned by the teachers. The interactive logs of an intelligent system are used to predict at-risk students and also to identify their reading difficulties [62]. The at-risk students are also predicted at different percentages of course length [63]. A multi stage approach is adopted to identify at-risk students during their learning process [64]. Various deep learning, ensemble, hybrid models are used to predict the at-risk students [31–34, 65, 52, 66]. The weight adjustment problems of neural networks are addressed using particle swarm optimization techniques [67]. To make the models transparent, they are made explainable in [38, 40, 42] which helps to explain the factors that positively and negatively affect the at risk student prediction.

3.1.3Features affecting the academic performance

The factors and their selection that affect the performance is another area of investigation [68–71]. An algorithm was developed in a study that happened in China which helps to select the discriminative features that are used in the predictive model [72]. It is found that the impact of teaching in the classroom environment is highly related to student performance [73]. Suggests that the more focus on feature importance should be given for better ML models [64]. Tries to find the selection attributes which will determine the success of a student in an undergraduate program [70]. The economic, academic, social, and behavioural factors which affect the early identification of at-risk students are studied [74]. In [75] students' performance evaluation in previous grades is considered along with age, school, address, family size, and activities to predict student performance using ML techniques. There are studies which tries to identify the factors that affect the academic performance of deaf students [76, 36, 44, 77, 78]. As student data is generated from various sources, a multi-source multi feature behavioural data is considered in prediction model [51]. An ensemble method that extracts feature categories of engagement, semantics and sentiment from a student dataset is also proposed [43]. A conceptual framework is proposed to find the nature of features selected, that is as latent attributes which cannot be controlled and the dynamic attributes which can be controlled by the students [79]. Explainability concepts are also used to identify the important features [39]. Statistical methods are also used for the feature selection to model the data efficiently [80]. For an effective ML model the selection of features are important which may influence the performance of model [81–85].

3.1.4Suitable course selection

Recommendation on selecting a new course is also developed using ML techniques. An adaptive recommendation system is suggested for a preparatory year student to select a suitable education path [86]. A recommender system that helps the student with suitable subject enrolment is proposed [87, 88, 55]. Learning management systems (LMS) are very popular and the data generated from these systems are widely used with ML techniques. In 2017, a comparison of 17 blended courses was done using Moodle LMS and at-risk students for each course are predicted [89]. Motivational comments and video recommendations are given to students which help them to choose the right subject and the comments give them insight into reasons for dropout [48].

Table 3 ML and EDM application for student performance analysis

Application	ID	No. of studies
Performance prediction before the course commencement	[33, 54, 56, 57]	5
Prediction of at-risk students	[31,32,34,65,38,40,41,42,52,67,63,66,62,60,90,91,61,58,59,64]	20
Features affecting the academic performance	[76,36,39,43,44,79,70,77,51,81,80,69,83,74,82,78,84,92,68,85,75,71,93,72]	24
Suitable Course selection	[87,86,55,88,89,48]	6
Prediction of marks / grades	[29,30,37,45,46,47,94,49,50,53,95,96,62,90,97,98,58,99,100,16,72,98,18,15,75,101,102,64]	28
Identifying the learning styles of students	[103–107]	5

3.1.5Prediction of marks and grades

Many studies tried to predict the marks in upcoming semesters [58, 52] and to categories the students depending on their academic achievements [108, 102]. The final-year grades are predicted with first-year marks [86]. A predictive model of Grade Point average is constructed [46] and probably helpful interventions are detected. The institutional, academic, demographic, psychological, and economic factors are used for student performance classification [90]. The relationship between academic records at the point of admission and the performance of students during the first year is studied [57]. The result of this study showed that not only the academic factors but also the non-academic factors along with personal lifestyle and struggles while they are in university also affect their performance in the first year. Using social media as a learning resource and time spent on it and its effect on performance are studied [91]. This is considered as a major application where several models are proposed as in *Table 3*.

3.1.6 Identifying the learning styles of students

According to the educational theorist Neil Fleming, there are four types of learning styles-visual, auditory, reading/writing preference, and kinesthetic. Identifying the learning style of a student and providing adequate instructions play an important role in the academic performance of a student. In learning analytics, this is an area of interest [105]. The studies on learning styles help to understand how a student acquires knowledge through an online medium [104]. Another classification of learning style is proposed by Felder Silverman as input, processing, perception, and understanding [93]. The inactivity of users and incompletion of courses are the major issues related to eLearning. It is necessary to understand each student's learning style to know their preferences in the learning process [106]. The data from eLearning activities are used with ML models to detect the learning style of a student.[103] tries to identify the learning style of a hearing-impaired student.

3.2Features and datasets used for performance analysis

RQ2.What features and datasets are used for performance analysis of students in general and deaf students in specific?

To predict the student performance in academics [109, 68] use the dataset from Kaggle. It has 16 features and 480 instances. This data is obtained from a LMS called Kalboard 360. The features used for classification belong to three categories-demographics features, academic background features, and behavioral features [59]. Uses the data collected from three different colleges in India. The dataset has 300 instances with 22 features. The features include academic features, demographic features, and family details. The performance of students in quizzes, assignments, and their behavior features in watching video lessons and reading learning materials in an LMS is considered for classification [110]. Along with gender and occupation of parents, class 10-mark percentage, class 12-mark percentage, the medium of instruction in school, and the syllabus followed in school are also considered [111] to classify the students in an entrance examination. The specific events that occurred during the interaction between the students and the system are used to classify the students into three groups based on performance [112]. It includes 9 features – number of front-page visits, downloads, submissions, accumulated, average and percentage scores, Time taken to finish each stage and each maze, and difficulty level selected. To predict the early identification of student retention and dropout, the preparatory and semester 1 features are considered [113]. The student grade prediction dataset from the University of California Irvine ML Repository which consists of 33 attributes with 1024 records is used to predict the grade [45]. The attributes include exam grades, social-demographic, and school-related features. To predict the performance of deaf students the same dataset is used but with 7 selected features [67]. The data of 525 students with 9 attributes are used [101] to classify the students. The features include individual marks in the entrance examination, total marks, high school location, gender, and gap year between high school graduation and the entrance exam. To predict freshman attrition the institutional data where the students are enrolled as a freshman during 6 years period is used. It consists of 34 variables and 21654 records [114].

The academic records of 335 students are used to predict the performance of computer science engineering students [115]. The dataset comprises a total of 68 subjects organized into seven subject areas Electronics, programming, and software development, information network infrastructure, databases, mathematics and physics, general education, languages, economy and administration. [116] tries to understand how the student's test scores is affected by the other variables-Gender, lunch, parent education, ethnicity, and test preparation course. The features used in different studies are summarized in *Table 4.*

Though there is a limitation in the opportunities for education for deaf students, the findings of the study [117] show that parents' obligations, expectations, and learning support provided to their deaf children at home influenced their children's academic achievement. Results also established that institutional barriers, such as effective instructional processes used in deaf education, availability of facilities, teaching, reading learning resources, and curricular content, all provided challenges to deaf students' academic achievement. Discusses the necessity of improving access, equity, policy, and practice of deaf faculty in higher education [118]. The mode of communication, the usage of sign language or speech, also affects the academic performance of deaf students [119]. The comparative study [120] on the academic performance of students with hearing and deaf students in an inclusive setup indicates the relevance of specialized methodologies and pedagogies that has to be followed by faculties to improve the performance of deaf students. The lower academic performance of deaf students is mainly due to inadequate language skills[78].In a significant study[121], Marschark et al. forecast the academic success of deaf pupils based on individual, residence, communication, and educational aspects. In [67] a prediction model is suggested to predict the class 10 marks of deaf students. Seven features were considered that includes age, school, guardian, study time, grade 1 marks, parent support, and extracurricular activities. The features exam grades, demographics, environmental region, school, course category, and course grade are considered to predict academic achievements [50].

Table 4 Features used in various applications

Features	ID	No of studies
Socio-economic	[90, 74, 72, 58, 91, 30, 85]	7
Demographics	[90,56,60,63,61,67,66,74,72,116,48,58,50,29,46,53,49,84,82,92,107,81,85,59,75,105]	26
Academic	[54,55,90,57,52,56,99,62,63,67,74,95,69,72,70,116,48,58,108,102,98,50,30,29,46,53,47,45,51,84,69,97,92,16,122,59,75,18,104,103]	40
Behavioural	[90,99,60,61,67,123,74,124,125,89,72,70,87,48,15,102,91,30,46,49,45,51,84,82,107,81,85,75,85,103,106,105,126,17]	34
eLearning activity	[62,63,95,125,89,68,30,45,122,126,106,127]	12

General conventional teaching methodologies are followed in most of the schools and colleges to teach deaf students. The absence of pedagogical experience adds to the challenges that deaf children confront in accessing appropriate educational services [128]. Prior academic achievement, student variables, and the student's eLearning engagement are the most influential elements in predicting academic success for any student [24]. Apart from these factors, deafness-related criteria may also have an impact on a deaf student's academic success. Knowing these variables influencing deaf kids' academic achievement may aid teachers in constructing tailored curriculum for them, allowing more deaf students to take advantage of available opportunities in higher education [129]. It is strongly suggested that deaf students attend regular schools, but this will necessitate additional modifications tailored to their specific needs. The findings of research in this field point to accommodations that allow a student with hearing loss to participate in a regular class alongside hearing students. The features used in applications which analyse the academic performance of deaf students is summarised in *Table 5*.

The most commonly used open-access standardized dataset used in the ML applications in the education domain is from Kaggle and UCI data repository. Many studies use the dataset generated from institutional academic databases. Another source of data is the LMS and online courses. Questionnaires are also used to collect the data and then standardize it to a dataset suitable for ML applications. Feature selection and optimization is another area of interest. The demographic, social, economic, behavioral, and academic features are mainly considered. It is found that the open access dataset which comprises the details of deaf students is not available. The details of commonly used open-access datasets are summarized in *Table 6*.

Table 5 Features used in various applications which analyze the academic performance of deaf students

Features	ID
Parent influence, availability of facilities, teaching, reading learning materials	[117]
Teaching methodologies and pedagogies	[25]
Exam grades, demographics, environmental region, school, course category, and course grade	[50]
Learning preference and communication	[130,131,132]
Learning Style	[104]

3.3Explainability of models

RQ3. What are the advantages of using explainable models in this domain?

Ribeiro et al. ask the question "Why should I trust you?" indicating the importance of the explainability of a classifier [133]. This work is an attempt to make the black box models more transparent and trustworthy. The major advantage of explainability is that data can be backed with reasoning that will help the stakeholders to make better decisions. The novel explanation technique local interpretable model-agnostic explanations, LIME is proposed in this study which gives an explanation made by any classifier by learning an interpretable model locally around the predictions. In the systematic survey, different perspectives of explainability are explored. It is found to be a good model that should be able to justify, control, improve and discover [134]. Tries to review the factors influencing student predictions and the various explainable techniques that make the model results interpretable [135]. This study recommends the use of a customized interpretable dashboard for the instructors to comprehend the model results. It also needs to consider the constraints related to privacy of data, confidentiality, fairness, and accountability of the model and also, model interpretability [136].

When it comes to the education domain, the need for explainable and interpretable models is very vital. Models with properly quantified and evaluated accuracy and explainability are much needed for student performance predictor models [137]. The stakeholders of the system should be given predictions with explanations that can improve the effectiveness of feedback. For adding expressiveness to the models, graphical tools are required [112]. Shapley values, often referred to as SHAP values, of the features are also used to interpret the model prediction [138]. For better policy-making and improving student performance, the stakeholders of education can use data backed by reasoning.

Table 6 Details of commonly available open access datasets

Dataset	Description	ID
Students' Academic Performance Dataset (xAPI-Edu-Data) https://www.kaggle.com/aljarah/xAPI-Edu-Data	16 features and 480 instances Data obtained from LMS-Kalboard 360 Demographic features, academic background features, and behavioural features	[139,140,109,138]
Student Performance Dataset https://archive.ics.uci.edu/ml/datasets/student+performance	33 attributes with 1024 records Student grades, demographic, social, and school-related	[30,67,45]

	features	
Student Performance Dataset https://www.kaggle.com/adithyabshetty100/student-performance	8 attributes with 1000 records Gender, race/ethnicity, education level of parents, lunch, test preparation time, the score obtained in Maths, reading, and writing	[83]

In [110] learning analytics, an explainable ML strategy has been given to predict the achievement of students at an assessment level and to discover the variables that influence student performance. The study also proposes a dashboard that gives effective feedback that helps the student to self-regulate his learning. Most of the recent studies use deep learning models to predict student performance. The explainability of these models is not further considered [137]. This survey clearly states that there exists a huge need for research on the explainable Though many types of research were carried out in the education domain with different individual, ensemble, and hybrid models predicting the students' performance, identifying at-risk students, and identifying factors affecting the performance, the studies that deal with the explainability of these models are very limited. As the advantages of explainable models are popularly known it calls for further research in this area. All the stakeholders of the education will benefit from the transparent models which further improve the trust in the model. LIME is one of the techniques which are widely used to make localized explanations that further help in making reasoned and informed decision making. LIME employs a representation that is understandable by humans, regardless of the model's actual features which are called interpretable representations.

This study acknowledges certain limitations. Firstly, the under-reporting of research on deaf students raises concerns about the generalizability of findings and the development of tailored strategies. The absence of benchmark data compromises comparability, and the need for interpretability in existing methods may impact their acceptance. Lastly, while findings aim to benefit various stakeholders, there's a need to explore potential variations in stakeholder interpretation and utilization for practical applicability.

4.Critical review of results

To address the research problems identified studies addressing the problems under review are collected. The problems, solutions, and gaps were identified in the studies. The application-wise distribution shows

models that predict student performance and also the need for their evaluation metrics. The need for personalized explainable models is shown by [141] so that feedback from the intelligent tutoring system can increase the trust of students in feedback. LIME algorithm is the commonly used algorithm used to cluster the students based on their academic attainments [142] and to find the actual success indicators for specific students, localized models are important.

that the majority of applications addressed the prediction of marks and grades (32%) and the features affecting the academic performance (27%). Both these issues are vital in ensuring a better education environment for a student. The distribution is shown in *Figure 4.* As shown in *Figure 5*, prediction, and classification methods are used in the majority of applications. Only 7% of studies tried to bring transparency in predictions by including explainability concepts. Around 54% of studies use ML techniques of which 30% use deep learning techniques as represented in *Figure 6*. The neural network models (20%) and hybrid models (18%) are mainly used in these applications. The distribution is represented graphically in *Figure 7*. 89% of studies deal with issues in the education domain in general while only 11% of studies deal with issues specifically in the deaf education domain as shown in *Figure 8.*

To identify the research trend in this domain, the citations of works under consideration are analyzed. The bubble charts regarding the same are represented in *Figure 9* and *Figure 10*. It is observed that works with greatest citations are [59, 89, 85]. Though majority of work in this domain happened in 2019, there are considerable researches in 2021 and 2023.This implies that the researchers are focusing on the ML based applications that would make an impact on the society. The study reveals the role of ML and EDM applications in student performance analysis. The major issues addressed by ML and EDM are the prediction of final grades, identification of at-risk students, and the factors that affect the student performance. The feedback using these models is very useful and leads to the development of recommendation systems that help the stakeholders of education. The improvement of these recommendation systems is one of the areas of interest in recent research. The visual representation of feedback in the form of dashboards contributes to the improvement of the effectiveness of such systems. This calls for the need for explainable models which build the trust of stakeholders in the system [133]. There exists a research gap that needs to be addressed by developing interpretable and explainable models in educational applications.

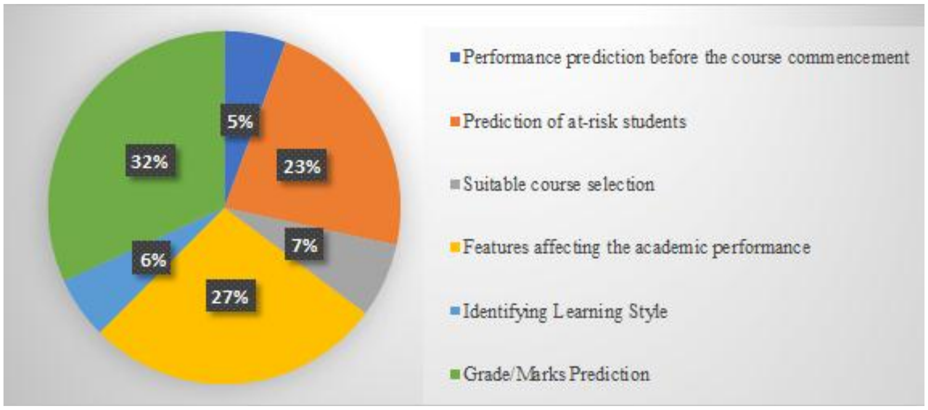

Figure 4 Application-wise distribution of included publications

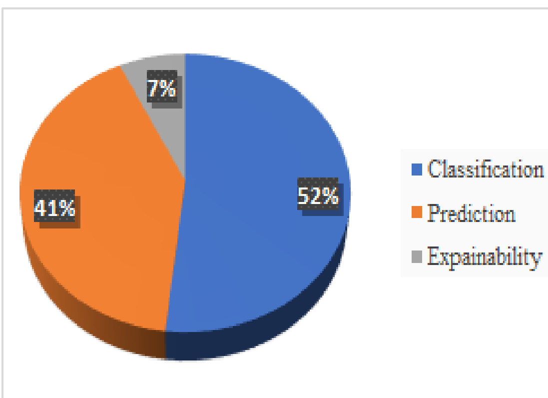

Figure 5 Frequently used methods in included publications

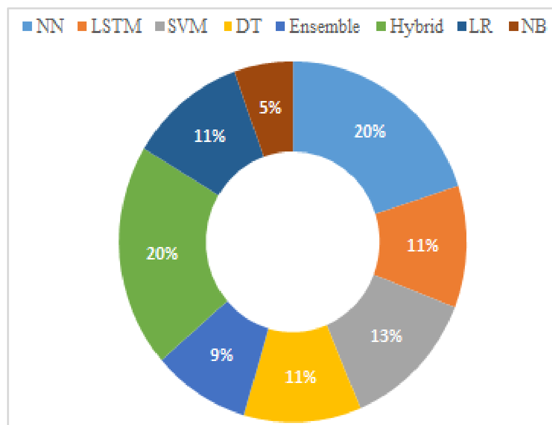

Figure 7 Models used in applications

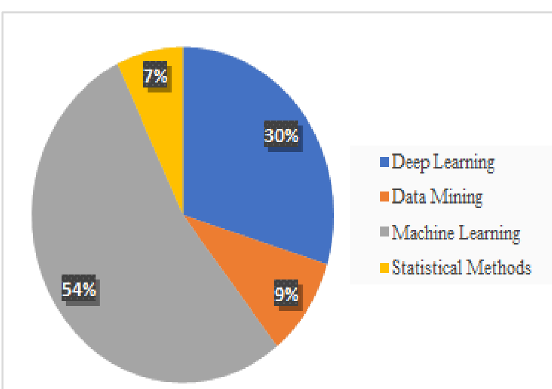

Figure 6 AI techniques used in applications

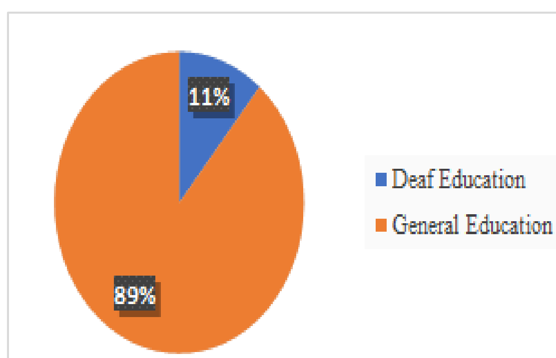

Figure 8 Distribution of General and Deaf education-related publications

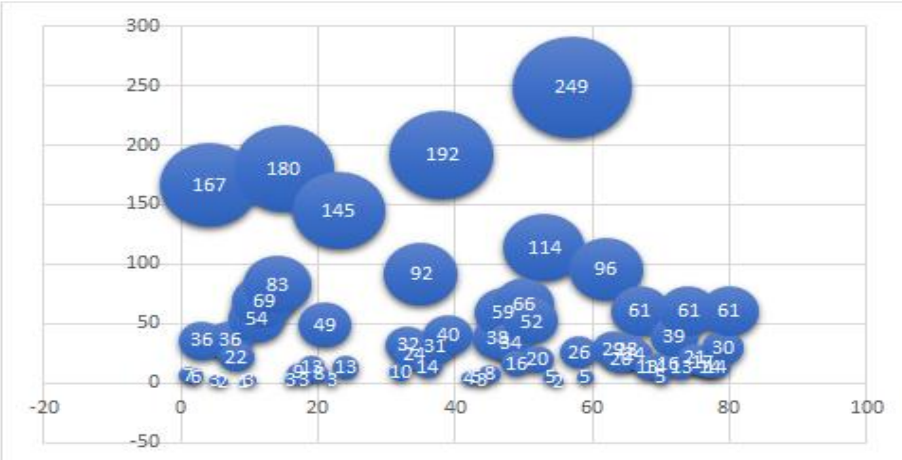

Figure 9 Distribution of publication citations

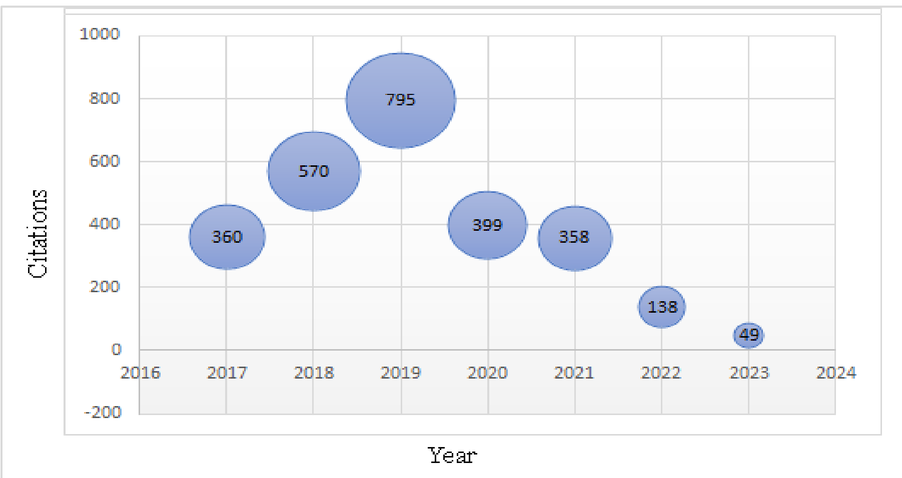

Figure 10 Year wise distribution of publication citations

The review tried to explore related works in the area of deaf education. It is seen that only 11% of the studies considered deal with deaf students. Analyzing the available works, it is seen that Institutional challenges like effective instructional processes employed in deaf education, facility limitations, teaching, reading and learning resources, and curriculum, all have an impact on deaf students' academic success[117]. Identifies the need for methodologies and pedagogies to follow in deaf education considering their special needs [143]. Reveals that the time series analysis algorithm may reliably predict academic achievement and provide an enhanced comprehension of the advancement of deaf and hard-of-hearing learners [50].

Most of the works consider statistical methods to evaluate the academic performance of deaf scholars. This calls for new improved deep learning and ML models that can predict the academic performance of deaf scholars which in turn can improve their opportunities of higher education.

A more detail analysis of the recent works is done considering the period, 2021 to 2023. It is also observed that though many benchmark datasets are openly available online, a standardized dataset that comprises features unique to deaf students is not available. This can be one of the reasons that put a limitation to the research in this area. Deafness is considered a unique disability as it affects communication [144]. As the accessibility options are very limited for deaf students, they have limited opportunities for higher education. This affects the quality of their life. A huge research gap exists in this area as there are unique factors that affect the performance of a deaf student [121]. When the studies from 2021 to 2023 are considered, it is found that the majority of research in this area shows a trend toward deep learning techniques, and most of the works use hybrid models for prediction and classification. Hybrid deep learning models enhance the modelling process in terms of computation, functionality, resilience, and accuracy. From the major works listed in *Table 2*, the significant performance is resulted in [34,40,45,50,53]. These studies show that the performance accuracy of the models can be very high, though it depends on the dataset quality. Most of these studies use oversampling methods to balance the data and feature selection methods to select the significant features that contribute to the model prediction performance. The performance significance of each of these studies is tabulated in *Table 7*. From the review of these literature, a conceptual diagram is made which is represented in *Figure 11*.

Table 7 Analysis of studies with significant performance

Reference	**Performance**
[34]	• Hybrid Ensemble Model • Performance Accuracy – 98.4% • Demographic and Academic Features considered • Web Application based on the model developed
[40]	• Different feature selection methods employed • SMOTE-Tomek Sampling approach proposed to balance the dataset • Random Forest is found to be better performing model with an average accuracy rate of 99.6% • Local and global interpretation to the predictions is obtained using LIME and SHAP
[45]	• BiLSTM with Attention mechanism is used for classification • Performance Accuracy - 90.16% • Prior academic data is used for prediction
[50]	• Dataset size is high with details of 700K deaf and Hard of Hearing students • Used Deep Laerning LSTM model for prediction • Found that student grades, demographics, geographical region, school, course type, and course score are high correlation for predicting academic outcomes • Religious curricula, Arabic language, and mathematics act as influential predictive indicators of success or failure in the result.
[53]	• Multiclass prediction model with F1 Score 99,5% • Feature selection methods are used for significant features • SMOTE Oversampling is used for balancing dataset.

The research gaps identified based on the RQs are tabulated in *Table 8*. Based on the identified research gaps the framework represented in the block diagram *Figure 12* is proposed. The block diagram is represented in modules and submodules. The module 1 addresses the research gap1 which is the development and standardization of dataset with data related to deaf students. It has different submodules like data collection, data pre-processing, data standardisation, data privacy and ethics. The data can be collected from higher education institutions exclusively for deaf and also from colleges with integrated setup. The tools used for data collection is also need to be considered. For questionnaires and consent forms, the sign language videos along with the written format need to be provided considering the language difficulties of this population. Measures should be taken to secure data privacy. For the analysis of data, proper pre-processing and standardising techniques need to be used. For dataset publication in open portal, it should be assured that no sensitive or private information is included which can identify the participant. The module 2 is aimed to identify the factors that affect the academic performance of deaf scholars. The factors can be socio economic, deafness related, demographics, clinical factors and academic factors. The development of model is considered in module 3. It includes feature engineering, modelling using deep learning models, training and validation and evaluation of model using various parameters like accuracy, precision, recall and F1 score. The module 4 deals with explainability techniques. This can make the predictions transparent to the stakeholders of this model. Module4 represents front end development and deployment. An application with a user-friendly front end is much needed for the usage of this model by the stakeholders. It should be able to provide insights and feedbacks that can benefit all the users.

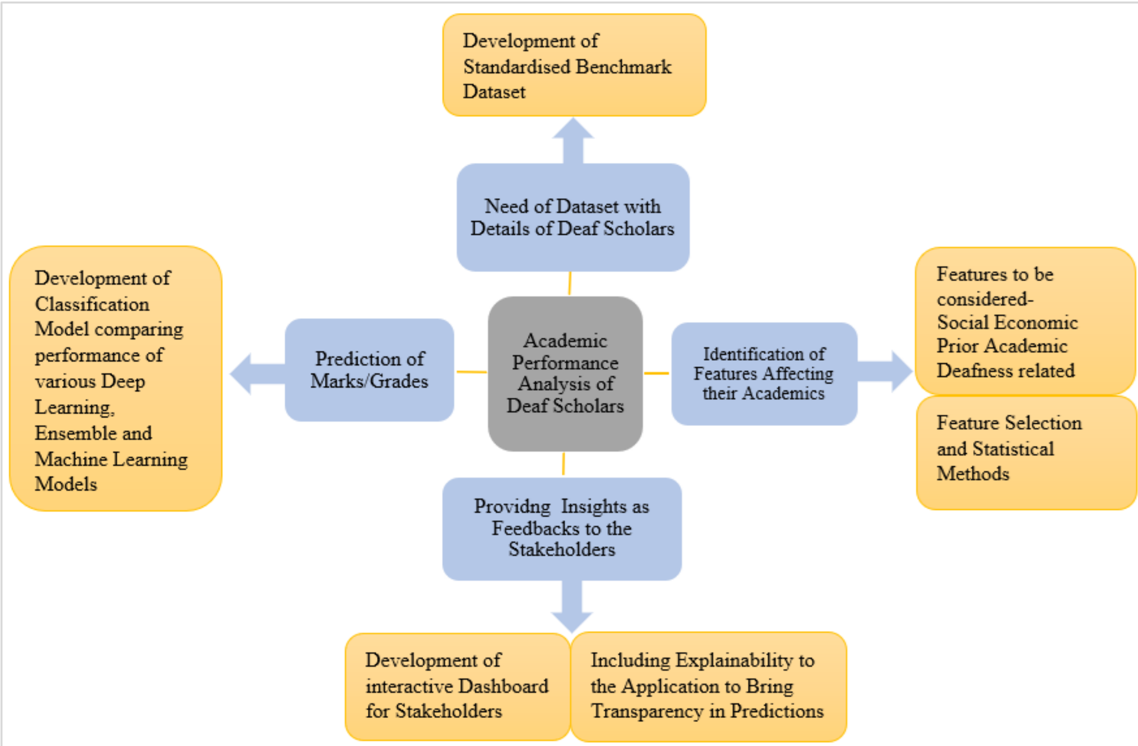

Figure 11 Conceptual framework based on literature review

Table 8 Research gaps identified based on RQs

S. No.	Gaps Identified
1	Need for development and standardization of dataset with data related to deaf students including the deafness-related features
2	Identification of factors affecting the performance of deaf students in academics
3	Performance analysis of deaf students using an efficient deep learning hybrid model
4	Developing an explainable model which gives valuable feedback to the stakeholders of deaf education.

5. Conclusion

Education helps the career growth and personal growth of a human being. It provides him confidence that may help him to succeed in all fields of life. The advent of technology and ML needs to be applied to make education more accessible and effective even for the minority. An attempt was made to comprehend the various reported research works using ML and data mining techniques in the education domain that happened from 2017 to 2023. Through a systematic approach, the research gaps that exist in this area were identified. The review was conducted based on five RQs. Though different models are proposed for addressing the issue of the education domain, recent researchers found that hybrid and ensemble models provide better models in terms of accuracy. The deep learning explainable models reported better results compared to other models. Performance improvement is always a topic of research interest. To conclude, there exists a research gap that needs to be addressed in the deaf education area. There is an urgent need to identify the factors affecting deaf students in higher education. ML and deep learning methods can be utilized within academia to predict constructive feedback about deaf student's performance. These advances will improve the quality of their education by providing effective, informative, and personalized feedback to the stakeholders of education. The major challenges and limitation faced by the researchers includes the availability of vast literature in general education domain and the scarcity of literature in deaf education domain. The non-availability of open datasets seems to be a major challenge in researches based on ML techniques in this domain. The research gaps identified open further researches in this area which can contribute significantly to the lives of deaf students.

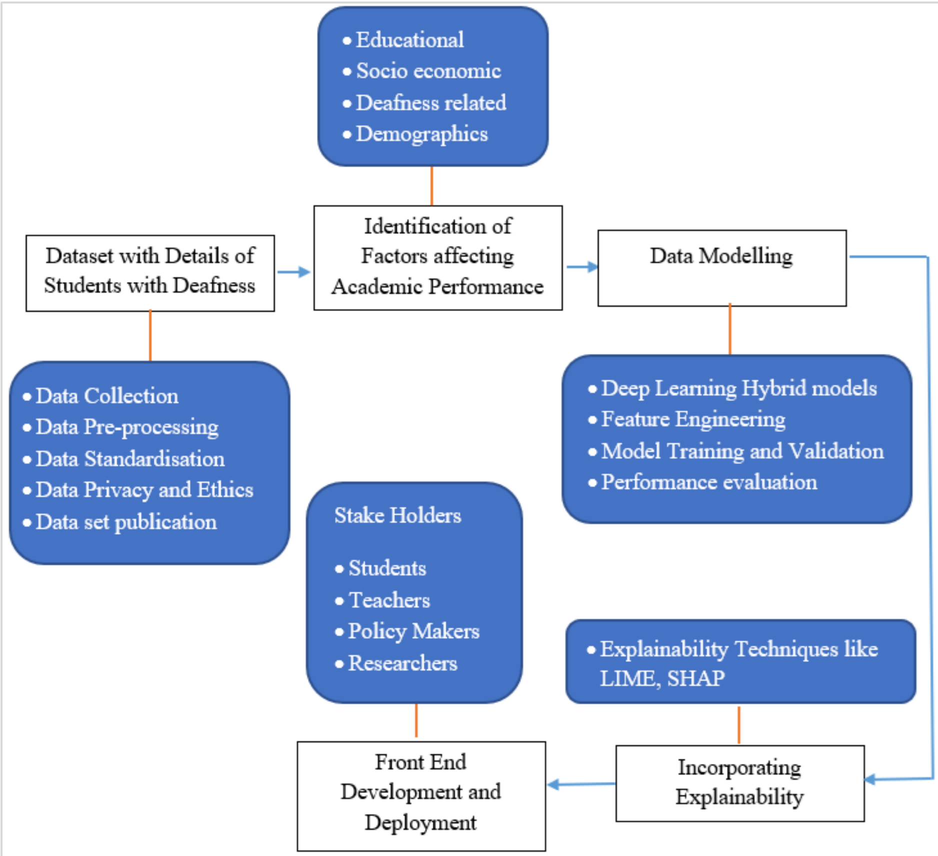

Figure 12 Block diagram of the proposed frame work based on the analysis

Acknowledgment
None.

Conflicts of interest
The authors have no conflicts of interest to declare.

Author's contribution statement
All the authors equally contributed in the following stages of this study: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

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Appendix I

S. No.	Abbreviation	Description
1	A	Analysis
2	ANN	Artificial Neural Network
3	C	Classification
4	Cl	Clustering
5	CNN	Convolutional Neural Network
6	CLDA	Cluster-Based Linear Discriminant Analysis
7	DL	Deep Learning
8	DM	DataMining
9	DNN	Deep Neural Network
10	DT	Decision Tree
11	E	Explainability
12	EDM	Educational Data Mining
13	GPA	Grade Point Average
14	GBM	Gradient Boost Machine
15	KNN	K Nearest Neighbor
16	LIME	Local Interpretable Model Agnostic Explanations
17	LMS	Learning Management System
18	LR	Logistic Regression
19	LSTM	Long Short Term Memory
20	ML	Machine Learning
21	MLP	MultiLayer Perceptron
22	NB	Naïve Bayes
23	NN	Neural Network
24	P	Prediction
25	PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
26	QAC	Quality Assessment Criteria
27	R	Regression
28	RF	Random Forest
29	RQ	Research Question
30	SVM	Support Vector Machine
31	WHO	World Health Organisation
32	XAI	Explainable Artificial Intelligence

Appendix II

Summary of studies under review

S. No.	Reference/ID	AI Technique	Algorithm/tools	Disability Features	Sample Size	Method	Citations
1	[29]	ML	LR, DT	No	90,000	P, C	13
2	[30]	ML	SVM	No	649	C	36
3	[31]	DL	ANN	No	641138	P	0
4	[32]	DL	Transformer	No	32,593	P	0
5	[33]	ML	RF, NB, SVM	No	275000	C	0
6	[34]	ML	SVM	No	555	C	0
7	[65]	DL	ANN	No	3.8M	C	0
8	[76]	SM	-	Yes	50	A	0
9	[36]	SM	-	Yes	25	A	0
10	[103]	ML, SM	DT	Yes	50	C	0
11	[104]	DL	MLP	Yes	82	C	2
12	[37]	DL	ANN	No	1854	C	96
13	[38]	ML	LR, RF	No	32593	C, P, E	3
14	[39]	ML	Minimally Counterfactual LIME	No	1738	E	6
15	[40]	ML	RF,LIME	No	32593	C, E	4
16	[41]	ML	LR	No	1723	P	5
17	[42]	ML	CatBoost, SHAP	No	4,624	P, E	14
18	[43]	ML	RF	No	4553	C	3
19	[44]	SM	-	Yes	22	Analysis	0
20	[45]	DL	BiLSTM	No	1044	P	36
21	[46]	DL	MLP+LSTM	No	46,670	P	10
22	[47]	DL	ANN	No	10140	P	29
23	[48]	DL	LDA+ANN	No	59279	C,P	20
24	[94]	ML	SVM	No	714	C	9
25	[79]	DL	ANN	No	151	C	2
26	[49]	DL	DNN	No	3,828,879	P	22
27	[105]	ML	XGBoost	No	396	C	3
28	[70]	ML	NB	No	-	C	8
29	[50]	DL	LSTM	Yes	700000	C	0

30	[77]	SM	-	Yes	14	A	0
31	[51]	DL	LSTM	No	3000	P	32
32	[52]	DL	DNN	No	4266	C	24
33	[81]	ML	J46+RF	No	400	C	13
34	[80]	DL	BiLSTM	No	4755256	P,E	1
35	[53]	ML	RF	No	1282	C	38
36	[67]	DL	NN	Yes	1000	P	3
37	[106]	ML	DT_+GBT	No	2048	P	8
38	[95]	DL	LSTM	No	668	P	54
39	[63]	ML	RF	No	32,593	P	59
40	[108]	ML	Subtractive Clustering	No	2000	Cl	5
41	[69]	ML	Hybrid Regression	No	3820	C,P	34
42	[83]	ML	Linear SVM	No	1000	C	49
43	[96]	ML	NB	No	525	P	26
44	[74]	ML	DT, ID3, RF	No	2560	P	5
45	[87]	ML	RF	No	6948	C	16
46	[86]	ML	LR	No	2566	C	16
47	[66]	ML	DT	No	487	C	61
48	[82]	ML	Multiple regression model	No	395	P	39
49	[55]	DL	ANN	No	50000	P	92
50	[62]	ML	Ensemble	No	2123	C	13
51	[78]	SM	-	Yes	2208	Assoc	30
52	[84]	ML	Ensemble	No	486	P	3
53	[92]	ML	SVM	No	273	C	61
54	[60]	ML	SVM	No	240929	C	66
55	[90]	DL	ANN	No	481	C	28
56	[91]	DL	ANN	No	161	C	69
57	[97]	ML	RF	No	6100	C	52
58	[54]	ML	MultiInstance-MultiLabel KNN	No	393	P	21
59	[61]	ML	GBM	No	-	C	20
60	[98]	EDM, ML	CRISP-DM, Multiple Regression	No	478	P,R	61
61	[58]	DL	Cluster based architecture	No	-.	Cl	24
62	[56]	ML	AdaBoost	No	29700	C	145
63	[57]	ML	LR	No	1445	C, R	17
64	[99]	ML	RF	No	165715	C	167
65	[68]	DM	FS-BN algorithm	No	500	C	83
66	[85]	DM	J48	No	161	P	180
67	[100]	DM	MLP based method	No	3000	P	31
68	[59]	DM	RF	No	300	C	249
69	[16]	DL	BiLSTM	No	2000	C	14
70	[72]	ML	SVM	No	1296	C	13
71	[89]	DM	LR	No	4989	P	192
72	[18]	ML	Ensemble Model	No	1169	P	114
73	[15]	DM	MWDT	No	82	C	40
74	[75]	ML	DT	No	649	C	14
75	[71]	DL	Deep layer supported SVM	No	786	P	5
76	[93]	ML	DT	No	100	P	14
77	[107]	DL	SGD + MLP	No	1152	P	7
78	[101]	DL	ANN	No	525	C	0
79	[102]	ML	SVM	No	2000	C	0
80	[88]	ML	KNN	No	92	C	3
81	[64]	ML	RF	No	13368	C	51