Application of machine learning in higher education to assess student academic performance, at-risk, and attrition: a meta-analysis of literature

Application of Machine Learning in Higher Education to Assess Student Academic Performance, At-risk, and Attrition: A Meta-Analysis of Literature

Abstract

Recently, the field of machine learning (ML) has evolved and finds its application in higher education (HE) for various data analysis. Studies have shown that such an emerging field in educational technology provides meaningful insights into several dimensions of educational quality. An in-depth analysis of the application of ML could have a positive impact on the HE sector. However, there is a scarcity of a systematic review of HE literature to gain from the overarching trends and patterns discovered using ML. This paper conducts a systematic review and meta-analyses of research studies that have reported on the application of ML in HE. The differentiating factors of this study are primarily vested in the meta-analyses including a specific focus on student academic performance, at-risk, and attrition in HE. Our detailed investigation adopts an evidence-based framework called PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) for reporting the findings of our systematic review and meta-analyses of literature on the use of ML models, algorithms, evaluation metrics, and other criteria including demographics for assessing student academic performance, at-risk and attrition in HE. After undergoing the PRISMA steps such as selection criteria and filtering, we arrive at a narrowed down dataset of 89 relevant studies published from 2010 to 2020 for an in-depth analysis. The results not only show the outcomes of the quantitative analysis of the application of ML types, models, evaluation metrics, and other related demographics but also provide quality insights of publication patterns and future trends towards predicting and monitoring student academic progress in HE.

Keywords: Machine Learning, Higher Education, Systematic Literature Review, Meta-Analysis

1. Introduction

Today, higher education (HE) institutions are undergoing intense competition to acquire students around the world and are resorting to strategies for assessing and improving the academic performance of students with early intervention with at-risk students with an aim to retain them. In HE, educational technology is an emerging paradigm and effective data analysis is becoming a pivotal part of HE to develop timely strategies to support their objectives. The data for analysis is collected from the education setting. Different data analysis techniques are used to extract meaningful information from the variety of data, collected from an educational setting, to detect patterns, identify trends, provide data insights, and make decisions. Researchers are correlating novel data analysis methods like Machine Learning (ML) to facilitate educational operations. ML is a data analysis method that automates the process of data analysis by developing efficient algorithms. However, despite the increase in Machine Learning research, there is still a lack of comprehensive systematic literature analysis of the use of ML in the HE sector especially in the context of predicting student progress. Thus, this study aims to conduct a systematic literature review of the literature on the application of ML in HE. The focus of this systematic literature review is to analyse the literature where the ML techniques are only used to predict student at-risk, academic performance, and attrition in HE setting.

1.1 What is Machine Learning and Background?

ML is a subset of Artificial Intelligence (AI). ML made its debut in a checker-playing program. Data mining's been around since the 1930s; machine learning appears in the 1950s. This means the foundation of ML has been around for a while, however, only recently it has become commercialized due to advancements in technology and affordability, and the possibility of deployment of ML solutions. In the modern world of data computing and data analysis and computing, ML is the key that provides applications the ability to function intelligently (Sarker et al., 2021).

According to existing literature (Soobramoney & Singh, 2019), There are three main broad types of Machine learning: **supervised** learning, **unsupervised** learning, and **reinforcement** learning. Figure 1 shows different categories of ML and different types of algorithms. This study will explore whether these three types are used in the application of ML in HE with a focus on student at-risk, academic performance, and attrition.

Supervised Learning: The supervised learning develops models based on both input and output data. It trains the learning model on a T training set with *n* number of training datapoints consists of input(*i*)-output(*o*) pairs i.e. $T= \{i_k, o_k\}$ where $1 \leq k \leq n$ (Murphy, 2012). Supervised learning uses trained labelled data to predict the labels of the unknown data. It is considered as a task-driven approach i.e. a model that achieves a task (classify or predict) by identifying the target from a set of labeled input (Sarker et al., 2020). Classification and Regression are considered supervised learning methods.

Decision Tree (DT), K-nearest Neighbor(KNN), Logistic Regression(LR), Support Vector Machine(SVM), Random Forest(RF), Linear Regression and Polynomial Regression, Naive Bayes(NB), Artificial Neural Networks (ANN) are few common supervised ML models.

Unsupervised Learning: Unsupervised learning analyse the unlabeled dataset with only inputs without the need for human interference. It develops the learning model on a T training set with *n* number of datapoints consists of only input(*i*) i.e. $T= \{i_k\}$ where $1 \leq k \leq n$ (Murphy, 2012). It is considered as a data-driven approach i.e., a model achieves a task by extracting meaningful knowledge like similarities, relationships, differences, or patterns from unlabeled data. Clustering and Association rule and Dimensionality reduction are regarded as unsupervised learning algorithms. K-Means, Frequent Pattern growth, Mean-shift, Gaussian models, and Principal component analysis are the example models.

Reinforcement Learning: Reinforcement learning develops a model that learns to react to the environment and contexts. It is considered an environment-driven approach as it achieves a task in an interactive environment and automatically improves its efficiency by evaluating the actions and experiences and learning from feedback from its own behavior(Nandy & Biswas, 2018) (Kaelbling et al., 1996). Similar to supervised learning, it develops the model on a T training set with *n* number of training datapoints consists of input(*i*)-output(*o*) pairs i.e. $T= \{i_k, o_k\}$ where $1 \leq k \leq n$ (Murphy, 2012). However, in Reinforcement learning, instead of giving the correct set of actions, the model decides from its experience what action to perform to accomplish the task by rewarding or punishing. Q-learning, Deterministic Policy Gradient, SARSA (State-Action-Reward-State-Action) are examples of reinforcement learning models.

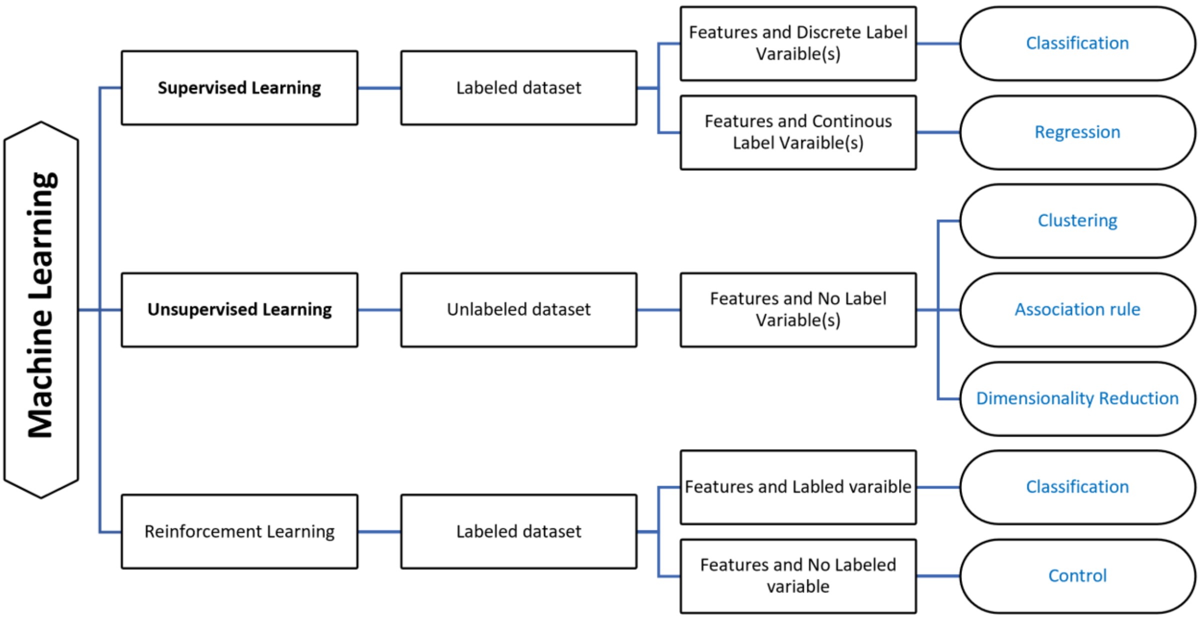

Figure 1: Different types of ML learning types and Models

Educational data originates primarily from student enrolment, student pre-enrolment activities, student transcript, class attendance and participation, assessments, and Learning Management System (LMS) while demonstrating student profile, actions, behavior, and academic progress. This review study will explore the features used in the application of ML in HE with a focus on predicting student academic performance, at-risk, and attrition. ML has had extensive adoption in the field of computing for quite some time, as mentioned above and recently the implications have witnessed effectiveness through the application of data analytics. The extant literature highlights the usage, enhancement, and benefits of ML in the educational sector. In this regard, this paper investigates the studies from the body of research published in the most recent decade (2010 and 2020). Our paper is the first of its kind to conduct a systematic review and meta-analyses on the application of ML in HE literature with our key focus on student academic performance, at-risk, and attrition.

Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page et al., 2021) is a framework to guide the researcher to do a systematic literature review step-by-step i.e. the reason behind the review, the procedure author followed, and the report the findings. PRISMA is considered an instrument to gauge the quality of a systematic review. Not many existing review studies in the field on ML in HE has used PRISMA. This study has used the latest version of the PRISMA framework i.e., PRISMA 2020, which replaced the 2009 version and used both divisions of the framework.

The remainder of this paper is organized as follows. First, a brief comparison of previous reviews in the field of machine learning and HE is presented; Next section describes the methodology carried out to retrieve the papers reviewed in this study, including a quantitative and meta-analysis analysis of the papers gathered; Following this, the section reports the findings of the by describes the main ML types with the main datasets; Finally, discussion and conclusion section briefly discusses and concludes the information compiled during this review study.

2. Research significance and objectives

Student attrition is considered one of the crucial issues for HE institutions. Research studies (Beer & Lawson, 2016) frequently mentioned student academic progress as a key factor associated with student attrition. In the existing literature, various techniques are introduced to predict student academic progress or student at-risk (Shahiri et al., 2015). Educators can arrange academic support programs to provide beneficial advice to improve their academic performance and encourage them in accomplishing their education. Consequently, it will reduce the student attrition rate.

Recently, researchers have studied the literature to examine different aspects of the application of ML in HE to gain insights for monitoring student performance. Table 1 summarises the existing review studies related to predict and improve student academic performance using ML in HE. It has briefly captured the gaps of each reviewed study to state the limitation of each reviewed study. For example, the context or publishing era is too limited or too broad, or the literature review methodology (e.g., inclusion and exclusion criteria) is not clearly defined, or no framework is used for conducting meta-analysis and systematic literature review.

Study	Study Aim and Gaps
(Lynn & Emanuel, 2021)	This review study has explored the articles from 2010-2020 researched the use of data mining techniques to predict student's performance to find out the most suitable data mining technique.
	Gap: The study has clearly defined the search strategy, but exclusion and inclusion criteria are not defined. Also, only 5 databases are used to apply the search strategy and the primary focus of these databases is not education, which may affect the result of the study. Furthermore, the study has not followed the PRISMA approach.
(Namoun & Alshanqiti, 2021)	This review study systemically reviewed the studies from 2010 to 2020 focusing on the use of data mining techniques to predict the student academic performance from the learning outcomes by using PRISMA and PICO (Population, Intervention, Comparison, and Outcomes) framework.
	Gap: The study focus for data mining techniques in education is broad. Also, the reasoning of the exclusion based on irrelevant studies is not clearly defined.
(Guan et al., 2020)	This review study has reviewed the survey studies published from 2000 to 2019 to identify the historical research trends, opportunities, and challenges behind the adoption of AI and Deep Learning in the education sector.
	Gap: The period to review studies was too large i.e., 20 years. With the rapid advancement in AI technology, the quality of reporting may not be optimal. Also, the study did not use the PRISMA framework.
(Ifenthaler & Yau, 2020)	This systematic review study has studied the studies from 2013 to 2018 show the effective role of learning analytics in facilitating study success in HE by using the PRISMA framework.
	Gap: The study only focused on the experiential studies and provided the finding based on incomplete information. Selection of publications from a range of 5 years to review a rapidly evolving field may not provide optimal findings and may oversight important outcomes.
(Wood & Shirazi, 2020)	This review study systemically explored, reviewed, and synthesized the studies published between January 2006 and December 2018 by using the PRISMA approach. The review studies were about the use of audience response systems (ARS) with a focus on the student experience.
	Gap: The study focused on the student experience, not academic performance.
(Zhou & Ye, 2020)	The review study explored the studies on sentiment analysis in education from January 2010 to April 2020. The study revealed the future research prospects from studies published.
	Gap: The focus of the study is sentiment analysis, not student academic performance. Also, PRISMA has not used a review framework.
(Aldowah et al., 2019)	The study reviewed and synthesized articles publish from 2000 to 2017 on the application of educational data mining and learning analytics technologies in HE to solve learning problems.
	Gap: The published era considered in this study is too broad i.e., 17 years which may not provide optimal results. Furthermore, the study has not followed the PRISMA approach.
(Korkmaz & Correia, 2019)	To investigate the studies on the current trends of ML pervasive practices in Educational Technology and sheds a light on future trends published between 2007 and 2017

	Gap: The source of the studies are only journals which limits the findings. The review was not done by following the PRISMA framework.
(Zawacki-Richter et al., 2019)	A systematic survey was done on the studies published between 2007 and 2018 about AI applications in HE. The findings were discussed was in terms of authorship and publication patterns with future recommendations. The study followed the PRISMA framework.
	Gap: The review studied only used three database sources to search the journal articles only. The limitation of databases and journals may provide quality assurance but can restrict the insight.
(Dalipi et al., 2018)	A review study to explore the utilization of ML to predict and solve the student dropout issue in MOOC (Massive Open Online Courses) setting. It reviewed the challenges behind this utilization highlighted in the studies published before 2018.
	Gap: The focus of the study is only on the MOOC setting and excluded courses that have the same characteristics as MOOC setting to enrich the review. Exclusion and Inclusion criteria are not clear i.e. the beginning of the publication year is not given. The study has not followed the PRISMA approach.
(Mousavinasab et al., 2018)	The surveyed the studies from 2007 to 2017 about the Intelligent tutoring systems in the educational sector and investigate the attributes, applications, and evaluation methods for meta-analysis by using the PRISMA framework.
	Gap: The study does not include the latest publications after 2017 which is crucial for a rapidly advancing industry like the application of ML in the educational sector. Also, only one database is used for the searching strategy.
(Alyahyan & Düştegör, 2020)	The review study explored and reviewed the studies on the data mining application in HE published from 2015 to 2019. The focus of the review study is to predict academic success with predictive accuracy.
	Gap: The publications reviewed in the study are only from 5 years and there are no inclusion or exclusion criteria defined, which may affect the result of the study.

Table 1 - Summary of existing review studies on adoption ML in HE

ML showing promising advances in AI is a rapidly evolving area, and therefore there will always be a continuous requirement of meta-analysis of research findings until the gap in literature gets filled up and the field of research matures. Furthermore, the focus of the existing literature was not primarily on student academic performance, at-risk, and attrition. In addition, our study aims to provide not only a systematic review of the application of ML models and frameworks, and research methods but also deeper insights through meta-analyses. Therefore, this study attempts to take the initial steps to fill the existing gap in the literature. This study systematically classifies and discusses the focus of application of Machine learning studies on student academic performance, models and frameworks, and research methods employed in the HE sector. Besides, the study briefly identifies future research trends. The study does not demonstrate the correlation between ML and student academic performance or student retention.

Following are the objectives that describe concisely what this study aims to achieve. The study aims to:

1. Determine the soundness and quality of the dataset extracted from the literature that has examined the application of ML in HE with a focus on student academic performance, at-risk, and attrition.

2. Perform a systematic analysis of the demographic aspects of the extracted dataset.
3. Conduct meta-analyses through keyword analysis of the dataset for discovering usage patterns of different ML approaches, models, and research themes that have an impact on student academic performance, at-risk, and attrition.
4. Identify popular ML algorithms and evaluation metrics employed in HE and their features related to predicting and monitoring student academic progress and retention.

3. Methodology

In recent years, the application of ML in education has been falling under a wide spectrum of HE requirements such as: to forecast the performance of the student, predict enrolments, employment readiness prediction, career recommendation, sentiment analysis, intelligent and adaptive tutoring, improve assessment and feedback system, resource recommendation, and identify struggling students to determine attrition or retention rate. In this study, we only focus on ML application in the context of predicting and monitoring student academic progress. This study employs a systematic literature review (SLR) method to provide a comprehensive review and of the application of ML in HE as having an impact on student academic performance, at-risk, and attrition.

This systematic review is conducted in accordance with the PRISMA framework proposed by (Page et al., 2021). We systematically searched the scholarly studies related to the application of ML to predict student performance in peer-reviewed journals. The following figure shows the main steps, adapted from the PRISMA framework (Page et al., 2021), this review study has undertaken to achieve the objective.

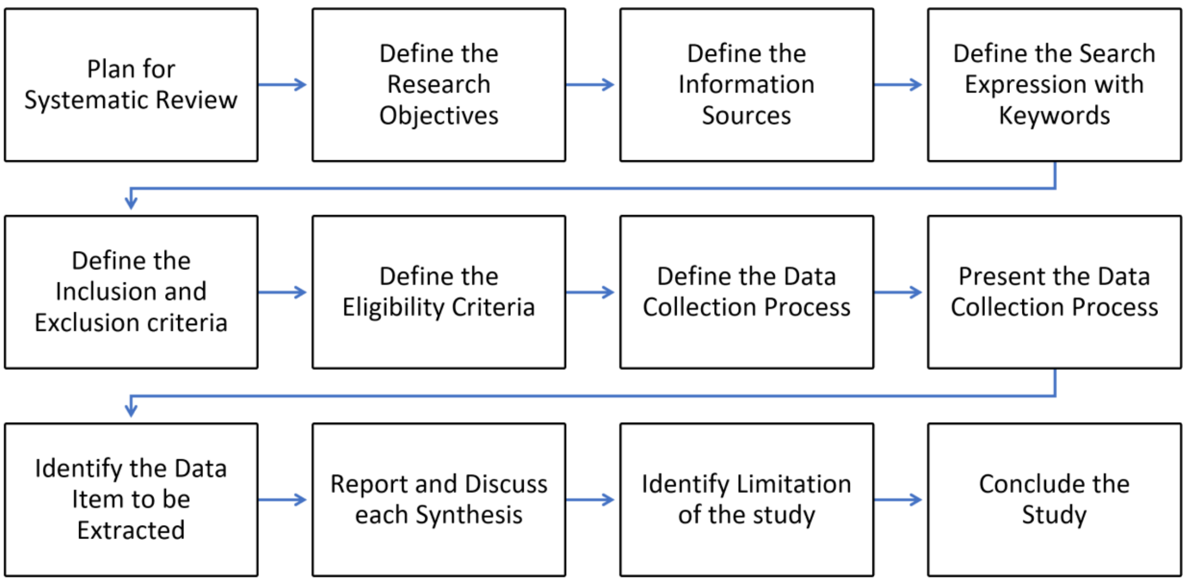

Figure 2: Process flow of the review study (adapted from PRISMA checklist) (Page et al., 2021)

The electronic databases are searched by preselected keywords and all literature is selected from well-known journals like Knowledge and Information Systems, Journal of Learning Analytics, Research in Higher Education, IEEE Transactions on Education, Decision Support System Decision Support Systems are few to mention. The output of the search results from the above-mentioned databases created the primary collection of the studies and are imported to reference management software, Endnote, and the required knowledge of the selected record is exported to the MS Excel spreadsheet. The required knowledge is either automatically generated from the metadata of the studies or manually retrieved and added to the spreadsheet. Then the title and abstract of the selected studies are screened by two reviewers based on inclusion and exclusion criteria. The inclusion and exclusion criteria are explained later in the section. Next, evaluation of the full text of the selected studies is done based on the eligibility criteria. The Figure demonstrates the selection and screening process of the studies selected in this review study.

3.1 Search strategy

Multiple databases were utilized to achieve the review objectives and search for the studies published between January 2010 and December 2020 inclusive. We explored the databases and selected the following educational research databases to conduct quality research in education search. The electronic databases are Scopus, Education Database, EBSCO, IEEE Xplore, ERIC, Web of science, Emerald Insight, Taylor and Francis, and ScienceDirect. The search was performed between May 2021 and June 2021.

Next, the search keywords were paired with Boolean operators AND and OR to combine the keywords or add the synonyms to create Boolean expressions. The keywords are selected to locate any studies focused on the research objectives. The keywords are: *"higher education", "machine learning"* ,*"student data"*,*"student learning"*,*"learning analytics"*, "machine learning", "tertiary education", "university", "higher education provider", "higher education institute", *"educational data"*. The Boolean expressions confirm that the search related to ML application only at the HE level. The search keywords are designed to form border criteria to retrieve the greater output of the search as much as possible.

3.2 Inclusion and Exclusion Criteria

The primary studies were selected to achieve the research objective by considering inclusion and exclusion criteria. The summary of the inclusion and exclusion criteria is given in Table 2. The search process was done from 2010 to 2020 and the language is limited to English only. Completed studies with full-text accessibility are only considered. Furthermore, duplicate studies are removed from the primary selected studies. Studies published in journals and conferences are considered and studies of other content types like a report, book notes, posters, PowerPoint, or book sections were excluded. Only research studies as primary studies are included and review studies are excluded. The exclusion is by searching the "review" *word in the title of the study.* The setting of the systematic review only focuses on the academic progress of the undergraduate or postgraduate students, therefore, studies from settings other than HE are excluded i.e. Secondary, middle, primary, or early learning settings. The perspective of the review is the application of the ML in the context of student performance only. Other contexts like educational recommendation systems, intelligent tutoring systems, or educational feedback systems are excluded.

Inclusion	Exclusion
Published between January 2010 – December 2020	Published outside the period of January 2010 – December 2020
Written in English	Not written in English
Primary studies	Not primary studies
Journal and conferences	Books, Slides, Notes, Posters, Reports
Tertiary education setting	Not HE setting
Complete and accessible full-text studies	Incomplete or inaccessible full-text studies
Unique Studies	Duplicate studies
Context is only about the application of ML about student at-risk, academic performance, and attrition	Studies that do not fall under student at-risk, academic performance, and attrition criteria
	No ML application

Table 2 – Inclusion and exclusion criteria of the review study

3.3 Selection process and inter-rater reliability

The studies screening procedure is carried out in 6 steps by following the recommendations from the PRISMA framework as shown in figure 2. The search expression output a total of 4,998 studies from the digital databases mentioned earlier. This framework has the following steps (1) Exclude the studies not written in English. Thus 28 studies are excluded as their abstracts are not written in the English language. (2) Exclude the duplicate studies by comparing the title, author, and publication year using Endnote. 1,493 redundant studies are removed. (3) Excluding the review studies and studies other than journals or conferences. 61 studies of the content type of abstract sections, books, news, grey literature, notes, posters, PowerPoint slides, workshops, reviews, indexes, and discussions are eliminated. 135 review studies were excluded. We have excluded the review studies while searching and collecting the studies in the digital databases. However, the filter option to exclude review studies was not available in all electronic databases. Therefore, we excluded the review studies by searching the "review" in the title of the studies. (4) Excluding the studies not relevant to the setting or context of this review. In this step, the first 2567 studies were removed by filtering in the Endnote, and then 565 studies were removed by manually screening the title and abstract of the remaining 711 studies as these studies were outside the HE setting and not in the context of Machine learning in HE. (5) Excluding the incomplete studies or their full-text is not accessible. 10 studies were eliminated in this step. (6) Excluding the studies based on the quality

criteria (explained later) by examining the full text. After this step, the metadata of the selected studies was tabulated by using a spreadsheet and reviewed by the reviewers.
After the initial selection, 146 potential studies are selected that meet all the criteria mentioned above and assessed in more detail by screening their full texts. The authors downloaded studies from literature and carefully extracted a dataset that were exclusively related to our research focus. The selection process adopted PRISMA's inclusion and exclusion criteria. It involved the inclusion of related studies and exclusion of non-related studies according to these eligibility criteria (1) Does the topic address in the study related to the application to ML in HE? (2) Does the context of the study relate to student academic performance or prediction of student at-risk or improve attrition rate? (3) Does the ML models and algorithms give in the study? While downloading the full texts, 10 studies could not be retrieved, therefore, 136 studies remained for eligibility criteria. A total of 49 studies are eliminated from the primary selection as they did not either satisfy the inclusion criteria or the eligibility criteria. Therefore, the remaining 89 studies formed the final selection for review analysis.

3.4 Data extraction and analysis

The final selection of the studies is examined to extract to achieve the objectives of the study. The Endnote application is used to extract the metadata about the study. The extracted data is imported in MS Excel. The metadata includes publication year, countries, author information, keywords, and journal the study is published in. Other required information like journal ranking or citation count of the study is added in the spreadsheet by exploring the web. Thereafter, data about the ML model, ML algorithms, ML evaluation matric, and dataset used to apply the ML model is identified by reading the studies thoroughly. The dataset for this review study consists of 13 features organized in the spreadsheet as given in Table 3.

	Feature Title	**Description**
1.	Research Title	Unique title of the study
2.	Author List	Name or names of the author of the study
3.	Year of Publication	Publication year of the study (2010-2020)
4.	Publication Media	Name of the journal or conference
5.	Journal Ranking	The recognized ranking of the journal (Q1 and Q4) in which the study is published for journal publications
6.	Citation	A total number of the citations of the study
7.	Research Focus	The main objective of the study
8.	ML type	The type of ML used in the study (supervised or unsupervised)
9.	ML Model	The category of the ML model(s) used in the study
10.	ML algorithms	The name(s) of the ML algorithms used in the study
11.	ML evaluation metrics	The name(s) used to evaluate the performance of the ML model used in the study
12.	ML accuracy	Highest accuracy percentage was achieved by the application of the ML model in the study
13.	Dataset	Features of the Dataset

Table 3 – Data accumulated about the selected studies

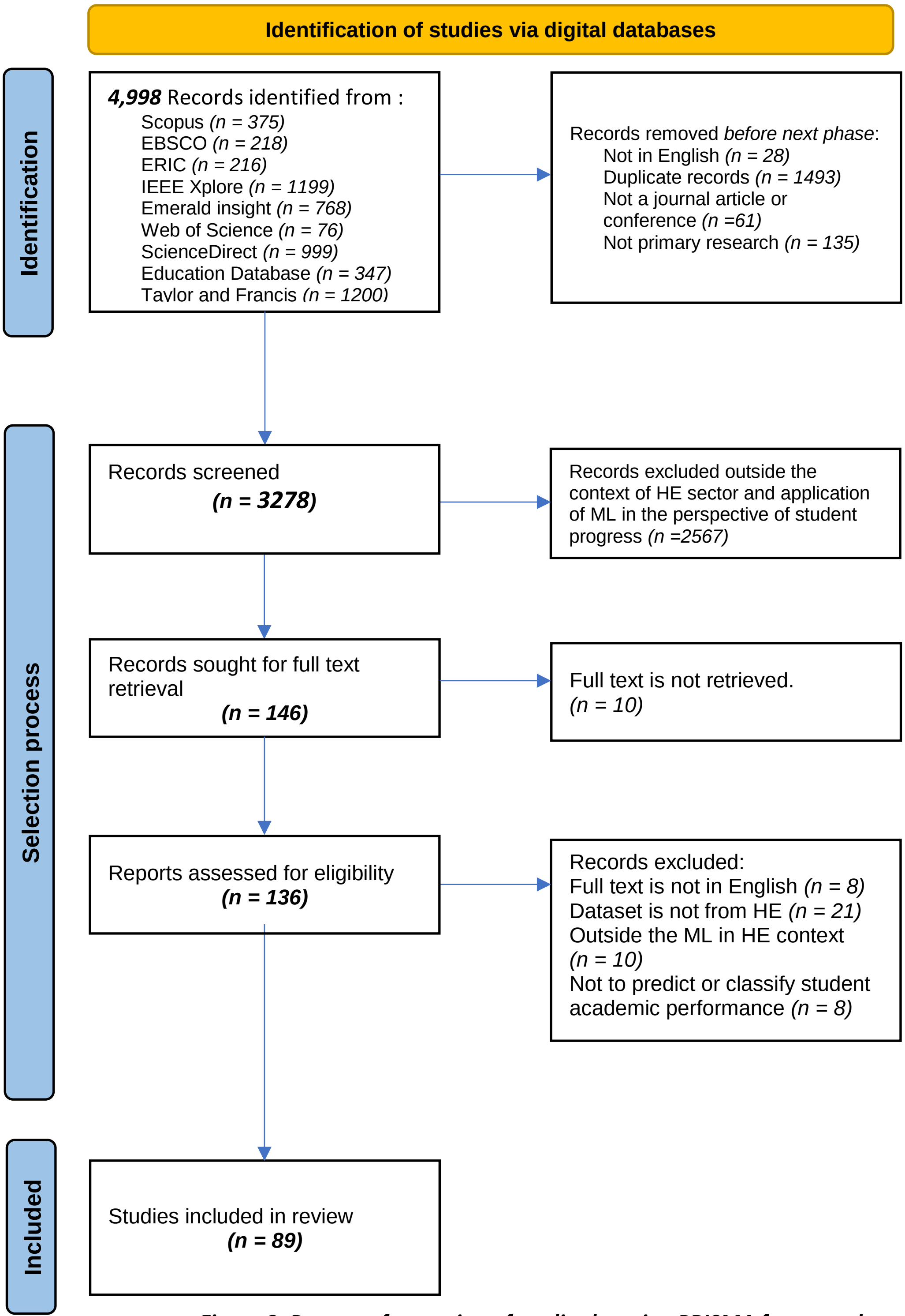

Figure 3: Process of screening of studies by using PRISMA framework.

3.5 Limitation

Though this review study is undertaken as systematically and meticulously as possible, it has a restricted search strategy which limits the scope of the review study. According to this search strategy, numerous large and well-known digital education research databases are elected to search for studies to be selected in this review study based on inclusion and exclusion criteria. Due to the search strategy, studies published in the same setting and context but languages other than English are not considered for this review. Likewise, similar research published not as a part of a journal or conference such as book chapters or grey literature is not included in this review study.

4. Findings and Discussion

This review study systemically analysed the rich information from literature in the educational realm with a focus on the application of ML towards a positive impact on student academic performance, at-risk, and attrition. This section reports the findings and discusses the discoveries by considering the research objectives of this review study.

4.1 Soundness and Quality Assurance of the dataset of the selected studies

A total of 57 journal publications and 32 conference studies are included in the selection. Out of 57 journal publications, 50% of the studies, are published in Q1 ranking journals. This finding shows the soundness of the selected studies that all studies are thoroughly research and reviews by technology and analytical field. The highest number of studies from the collection of selected studies that were published in one journal is 5 and are published in Education and Information Technologies, which is an educational journal. Table 4 lists the journals that published at least two studies on the application of ML in HE to monitor student academic progress from 2010 to 2020.

Rank	Journal Name	Studies count
Q1	Education and Information Technologies	5
Q1	Computers in Human Behavior	3
	International Journal of Modern Education and Computer Science	3
Q2	Computers and Education	2
	International Journal of Advanced Research in Computer Science	2
Q1	Journal of Learning Analytics	2
Q1	Physical Review Physics Education Research	2
	Procedia Computer Science	2
	Others with only one publication	68

Table 4: Distribution of studies by Journal

The citation figure shows the number of instances a study is cited by other studies. The following table (Table 5) contains the top cited studies in each year in the selected studies. The number of citations demonstrates the interest of researchers in the area of ML application in HE and motivates others to work in this area. Based on the ascending number of the citation per year, in future, more research studies are expected to emerge, and the interest will grow even more.

Year	Study	Cites	Journal
2020	(Chui et al., 2020)	58	Computers in Human Behavior
2019	(Gray & Perkins, 2019)	50	Computers and Education
2018	(Adejo & Connolly, 2018)	48	Journal of Applied Research in Higher Education
2017	(Hoffait & Schyns, 2017)	37	Decision Support Systems
2016	(Gray et al., 2016)	23	Journal of Learning Analytics
2015	(Biradar, 2015)	1	International Journal of Advanced Research in Computer Science
2014	(Trstenjak & Đonko, 2014)	13	2014 37th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)
2013	(Romero et al., 2013)	541	Computers and Education
2012	(Trandafili et al., 2012)	13	Proceedings of the Fifth Balkan Conference in Informatics
2011	(Delen, 2011)	50	Journal of College Student Retention
2010	(Delen, 2010)	119	Decision Support Systems

Table 5: Highest cited studies in each year

4.2 Demographics Synthesis of the Selected Studies

From January 2010 to December 2020, the publication rate of studies related to the application of ML models for monitoring student academic progress so that it never dropped to void. However, there were only a few papers published before 2017. Since then, there is a dramatic surge in the studies published reaching the peak of 32 in 2019. Figure 4 shows the article published per year from 2010 to 2020 on the application of ML in HE regarding monitoring student academic progress. The steady increasing trend line demonstrates the high potential of ML in HE to predict student at-risk, student academic performance, or attrition in future research.

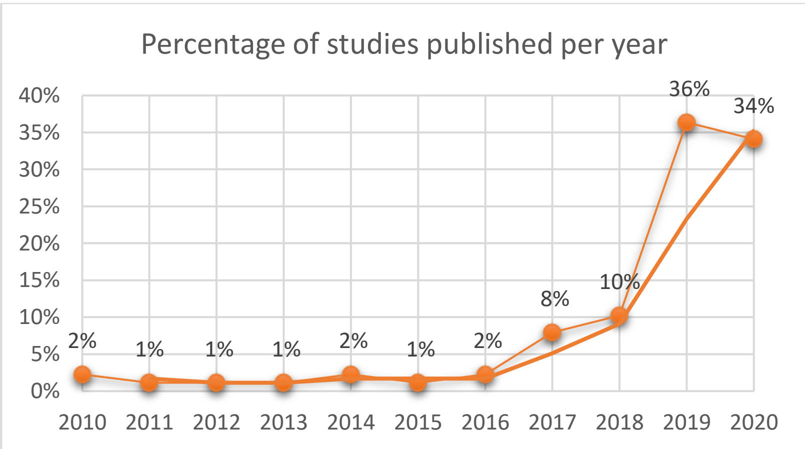

Figure 4: Distribution of studies by publication year

The country of the first author of the study is considered for the analysis of the geographical distribution of the studies selected. It is revealed that the US, China, and India are leading the research in the application of ML in HE with a focus on student at-risk, academic performance, and attrition, while South Africa follows very closely as shown in Figure 5. It is revealed that the top researcher country is the US where world highly renowned research institutes are located. There is a lack of research productivity from different countries throughout the world, this distribution motivates those countries to match the gap by researching in their educational environment about the application of ML to identify student performance, at-risk, and attrition.

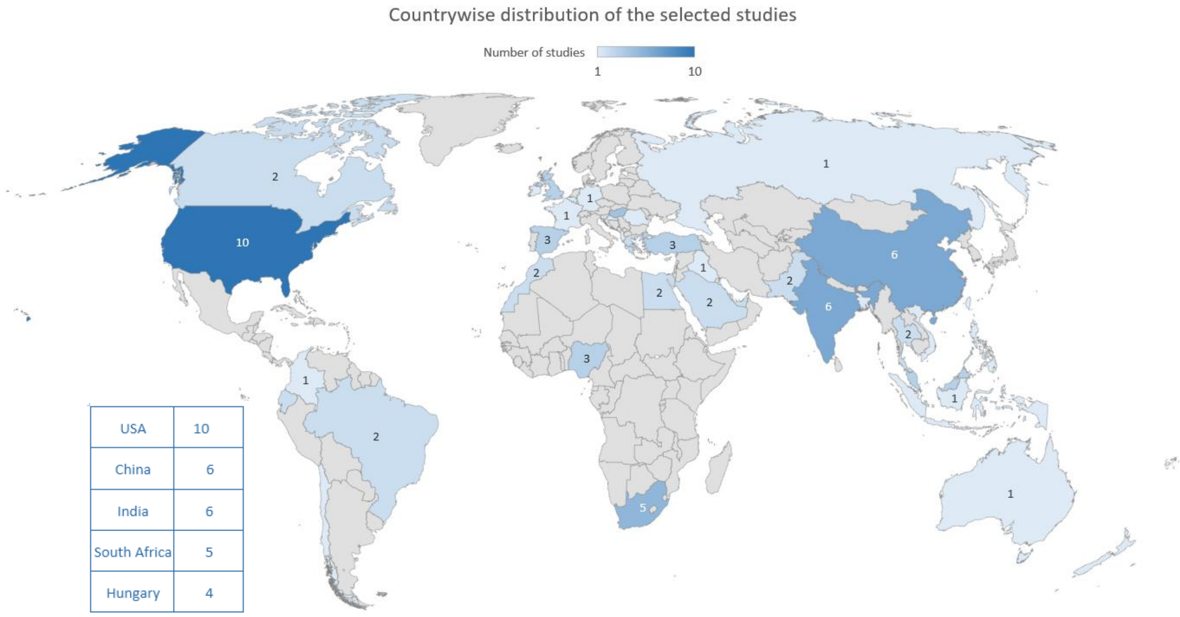

Figure 5: Distribution of studies by Country

These findings achieve the objective of identifying the demographic aspects of the selected studies on the application of ML research studies in HE regarding student academic performance and at-risk and attrition. The finding reveals that the area of application of ML in HE is emerging. There is a clear evolution in the research studies related to ML in HE related to study academic performance. This increase shows the growing use of information technology in education and can be of significant interest for researchers which implies more publications in the field.

Following figure 6 presents the distribution of the published study according to the number of authors of the study. It is clear that the majority of articles (approximately 50%) resulted from the collaboration of either two (25%) or four (23%) authors. In few studies were produced by collaborative research involving more than five authors. Only 9% of the studies were produced by the effort of an individual author.

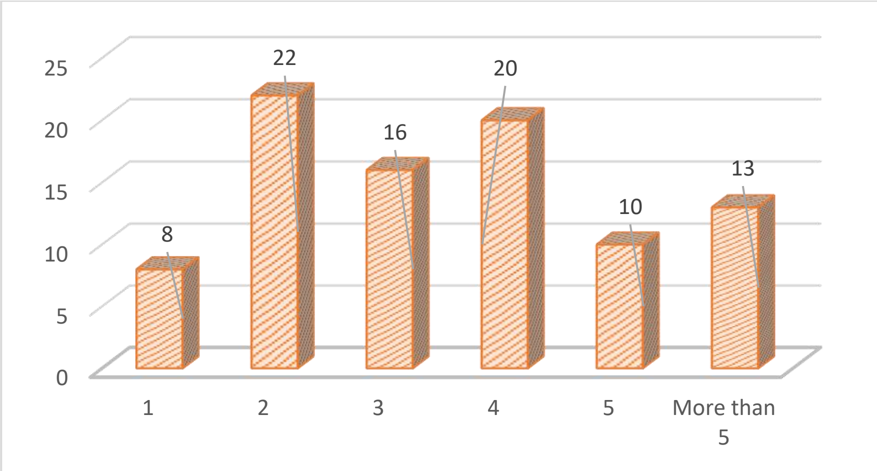

Figure 6: Distribution of studies by the number of authors

4.3 Keyword Analysis of the Selected Studies

Figure 7 displays the top keywords across the years based on their occurrence in the studies published in that year. The color intensity represents the appearance of each keyword during each year in the period of 2010-2020. The keywords are listed in descending order of their total count in the selected studies. It is obvious that the count of keywords is different each year. The top three words "Machine Learning", "Student success" and "Classification" are the keywords that almost remain in the keyword list throughout the period and appeared more at the end of the period. It can be also seen that a few keywords like "Support Vector Machine" and "Random Forest" appeared later in the period but have a strong appearance in studies. The keywords show the increased use of Support Vector Machine and Random Forest as for classification in recent studies.

Keywords	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020
Machine learning	3	1	1	7	12	18
Data mining	2	2	1	4	16	6
Artificial intelligence	1			3	6	4
Forecasting	1			3	9	9
Prediction	1			2	7	7
Learning algorithms				1	7	4

	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020
Classification	1		2	6	7	7
Decision Tree	1				13	9
Support Vector Machine			1	2	5	10
Random forest					7	10
Neural Network	1				6	4
Prediction model					8	3

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	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020
E-learning					5	3
Learning systems	1	1		2	10	5
Educational Data Mining		1	1	2	10	4
Education computing	1			1	6	7
Learning analytics					5	6

	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020
Drop out					4	5
At-Risk Students				1	8	7
Student success	1	1		4	16	18
Academic performance					8	6
Higher education	2			6	21	13
Online education					6	5

1

Figure 7: Top keywords appearance across the range of publication years

Out of 89 studies, it is revealed that the majority of the studies have used the feature of final GPA or final result as the target variable for supervised learning. Figure 8 shows the common features of the dataset used in the selected studies. Except for three, most of the studies indicated the number of features used to predict student academic performance or students at-risk. The number of features used to train ML models in the reviewed studies varied significantly e.g. one study (Beaulac & Rosenthal, 2019) only used 7 features to train the model, another study (Tenpipat & Akkarajitsakul, 2020) used 81 features, whereas, another study(Berriri et al., 2021) used 150 features. The features of the datasets in the reviewed studies are based on demographic and socio-economic background, pre-university, and university academic records, LMS interaction attributes. It has been observed the majority of the studies have used features based on demographic and socio-economic background, pre-university, and university academic records. Few studies have worked on LMS interaction features. There is still a wide range of student related features, for example, psychological attributes (motivation, interest, stress, or anxiety), which can be used and encourage the future researcher to contribute to predicting student at-risk, academic performance, and attrition.

Figure 8: Features of the dataset used to apply different ML algorithms in the selected studies

In addition, the instance size of the dataset used in the reviewed studies differs significantly. Figure 9 shows the distribution of studies based on the size of the dataset used to train the ML model. Only 6% of the reviewed studies did not reveal the size of the dataset they have used. The size of the sample dataset included in the reviewed studies as little as less than 100 instances (1%) and as large as more than 10,000 instances (29%).

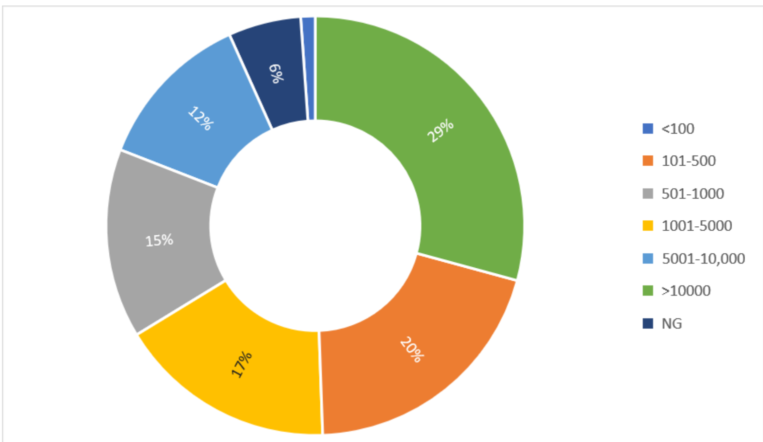

Figure 9: Distribution of studies by the size of dataset used in the selected studies

The above analysis of the keywords based on how many times they appear in papers in each period defined by year (shown in Figure 7) and significant features and size of the dataset used to apply ML algorithms (shown in Figure 8 and 9) accomplish the research objective of identifying the research themes with keyword analysis and explore the features of the dataset used for predictive models.

4.4 Analysis of the ML algorithms and the Evaluation Metrics

The majority of the studies, 88%, have applied supervised learning, whereas 6% out of the remaining 12% have applied only unsupervised learning. The remaining 6% of the studies have applied the combination of supervised and unsupervised learning to develop the ML model. The main purpose of the application of supervised learning was by using regression or classification to classify students based on their academic performance. The pie chart given in figure 10 shows the distribution of classification, regression, and clustering in the selected studies. It is discovered that classification models are most used (79%) for the identification of student performance in the years 2010-2020, followed by regression (12%) and clustering (8%). The classification model is based on deep learning and machine learning. Out of 79% fragment, 67% studies used ML algorithms, and 12% studies used Deep Learning algorithms to implement classification. It is obvious that most of the studies (90%) have used supervised learning and only limited studies (10%) have used unsupervised learning techniques. This identifies the lack of utilization of reinforcement learning models in this research area. This gap can be due to the nature of the reinforcement learning models. However, arises the need to research the adoption and application of reinforcement learning models to explore solutions to predict student at-risk, academic performance, and attrition.

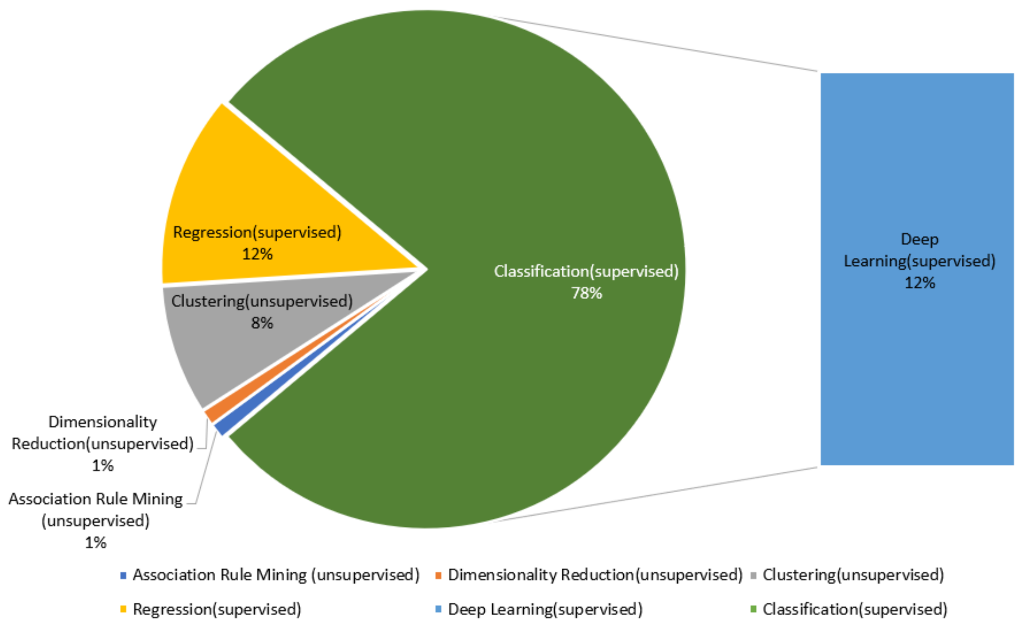

Figure 10: Division of studies based on different types of ML

The most used classification techniques are Random Forest, Naive Bayesian, Support Vector Machine, Decision Tree, and Boosting Algorithm. Linear regression and Logistic Regression algorithms are mainly used to apply regression models. Similarly, K-means is largely used for clustering. Figure 11 shows the used ML algorithms in the selected studies which are used in more than one study. It is revealed that Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), Naive Bayes (NB), Logistic Regression (LR), Artificial Neural Network (ANN), K-Nearest Neighbor (KNN), Gradient Boosted Trees (GBT), K-Mean, eXtreme Gradient Boosting (XGB) are the top ML algorithms used based on their recurrence in the selected studies. Few studies have mentioned that R programming language, Python, WEKA tool, and Rapid Miner tool are used to implement the ML algorithms.

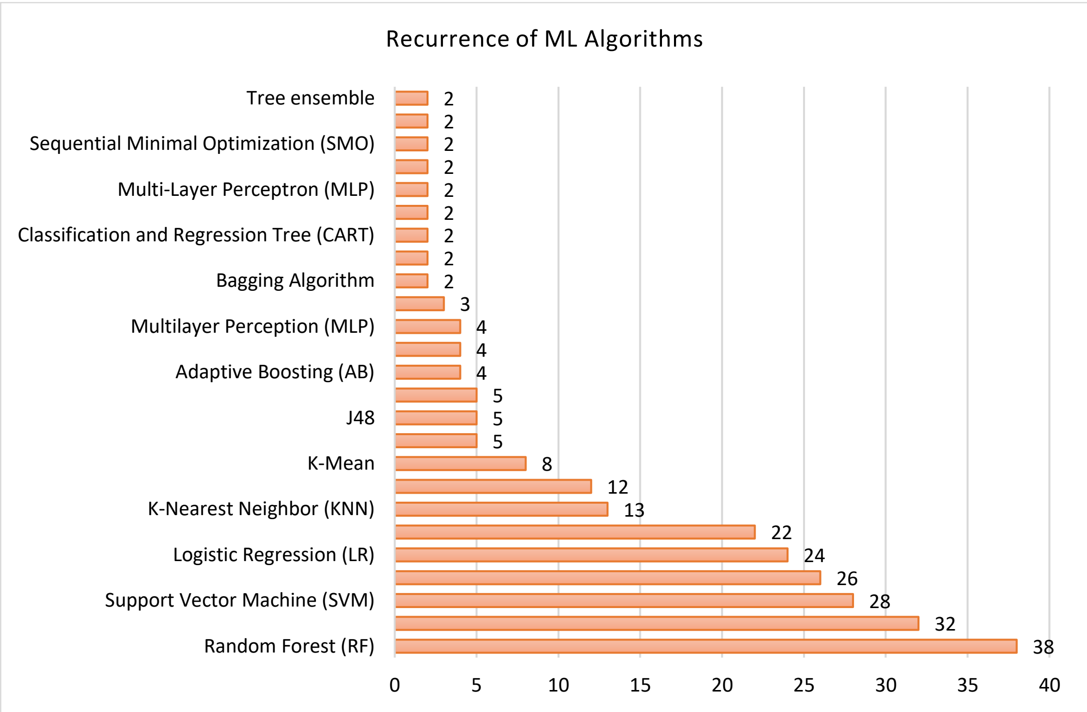

Figure 11: Recurrence of different ML algorithms

Multiple ML classification and regression models are built by using different algorithms. These algorithms are compared based on different evaluation metrics to identify the most appropriate ML model. These performance measures are evaluated mutually. Table 6 shows the predictive models and the evaluation metrics used in the selected studies. All evaluation metrics and algorithms are extracted if they are mentioned as the part of study regardless of the association between the algorithm and evaluation metric. For this purpose, this study has categorized the algorithms given in the selected studies as shown in Figure 12.

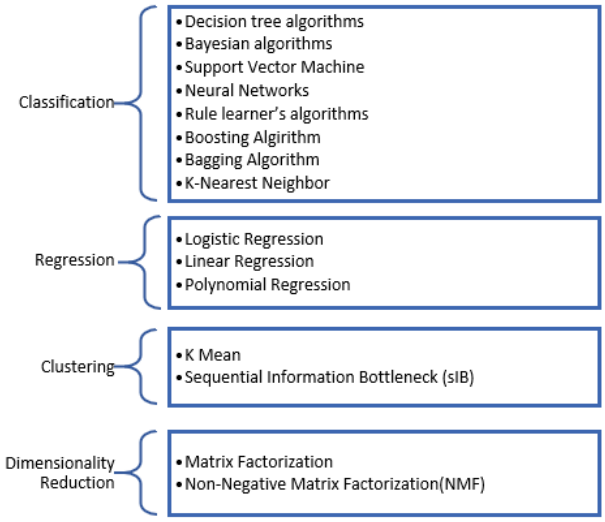

Figure 12: Categorizing different ML algorithms

Algorithms / Evaluation Metric	Decision trees	Bayesian algorithms	Support Vector Machine	Neural Networks	Boosting Algorithm	Bagging Algorithm	K-Nearest Neighbor	Logistic Regression	Linear Regression	Polynomial Regression	K Mean	Association rule	Matrix Factorization	NonNegative Matrix Factorization
Accuracy	(Adejo & Connolly, 2018; Aderibigbe & Noma-Osaghae, 2019; Al-kmali et al., 2020; Baneres et al., 2019; Beaulac & Rosenthal, 2019; Figueroa-Cañas & Sancho-Vinuesa, 2019; Francis & Suvanam Sasidhar, 2019; Freitas et al., 2020; Gamao & Gerardo, 2019; Gamie, Samir Abou El-Seoud, et al., 2019; Huang et al., 2020; Hutagaol & Suharjito, 2019; Iatrellis et al., 2021;	(Aderibigbe & Noma-Osaghae, 2019; Al-kmali et al., 2020; Baneres et al., 2019; Francis & Suvanam Sasidhar, 2019; Gamao & Gerardo, 2019; Goker & Bulbul, 2014; Huang et al., 2020; Hutagaol & Suharjito, 2019; Jayaraman et al., 2019; Kadhim & Hassan, 2020; Kamal & Ahuja, 2019; Mimis et al., 2019;	(Adejo & Connolly, 2018; Al-kmali et al., 2020; Baneres et al., 2019; Chui et al., 2020; Ciolacu et al., 2019; Francis & Suvanam Sasidhar, 2019; Freitas et al., 2020; Gamie, Samir Abou El-Seoud, et al., 2019; Huang et al., 2020; Jayaraman et al., 2019; Kamal & Ahuja, 2019; Md Rifatul Islam et al., 2019;	(Adejo & Connolly, 2018; Aderibigbe & Noma-Osaghae, 2019; Aydogdu, 2020; Baranyi et al., 2020; Ciolacu et al., 2019; Francis & Suvanam Sasidhar, 2019; Freitas et al., 2020; Gamie, Samir Abou El-Seoud, et al., 2019; Huang et al., 2020; Iyanda et al., 2018; Kadhim & Hassan, 2020; Kamal & Ahuja, 2019; Kiss	(Aderibigbe & Noma-Osaghae, 2019; Baranyi et al., 2020; Huang et al., 2020; Kamal & Ahuja, 2019; Kiss et al., 2019; Md Rifatul Islam et al., 2019; Mngadi et al., 2020; Oreshin et al., 2020; Santos et al., 2020; Tenpipat & Akkarajitsakul, 2020)		(Baneres et al., 2019; Freitas et al., 2020; Hutagaol & Suharjito, 2019; Md Rifatul Islam et al., 2019; Palacios et al., 2021; Raza et al., 2020; Romero et al., 2013; Santos et al., 2020; Wakelam et al., 2020; Youssef et al., 2019; Zeineddine et al., 2021)	(Aderibigbe & Noma-Osaghae, 2019; Choi et al., 2018; Freitas et al., 2020; Huang et al., 2020; Jayaraman et al., 2019; Ndou et al., 2020; Oreshin et al., 2020; Palacios et al., 2021; Ran et al., 2018; Raza et al., 2020; Waheed et al., 2020; Youssef et al., 2019; Zabriskie et al., 2019)	(Aderibigbe & Noma-Osaghae, 2019; Choi et al., 2018; Mngadi et al., 2020)	(Aderibigbe & Noma-Osaghae, 2019)	(Francis & Suvanam Sasidhar, 2019; Iatrellis et al., 2021; Romero et al., 2013; Zeineddine et al., 2021)		(Romero et al., 2013)	

	Jayaraman et al., 2019; Kadhim & Hassan, 2020; Kamal & Ahuja, 2019; Md Rifatul Islam et al., 2019; Mimis et al., 2019; Mngadi et al., 2020; Ndou et al., 2020; Oreshin et al., 2020; Palacios et al., 2021; Raza et al., 2020; Romero et al., 2013; Sani et al., 2020; Tenpipat & Akkarajitsakul, 2020; Trandafili et al., 2012; Wakelam et al., 2020; Xu et al., 2019; Yang et al., 2020; Youssef et al., 2019; Zabriskie et al., 2019)	Ndou et al., 2020; Palacios et al., 2021; Raza et al., 2020; Romero et al., 2013; Santos et al., 2020; Youssef et al., 2019; Zeineddine et al., 2021)	Mngadi et al., 2020; Ndou et al., 2020; Palacios et al., 2021; Pang et al., 2017; Raza et al., 2020; Romero et al., 2013; Santos et al., 2020; Waheed et al., 2020; Xu et al., 2019; Youssef et al., 2019)	et al., 2019; Mimis et al., 2019; Raza et al., 2020; Romero et al., 2013; Sani et al., 2020; Santos et al., 2020; Waheed et al., 2020; Xu et al., 2019; Yildiz Aybek & Okur, 2018; Zeineddine et al., 2021)										
Precision	(Adejo & Connolly, 2018; Al-kmali et al., 2020; Ashraf et al., 2018; Borrella et al., 2019; Chen et al., 2020; Figueroa-Cañas & Sancho-	(Al-kmali et al., 2020; Huang et al., 2020; Hutagaol & Suharjito, 2019; Philippou et al., 2020; Youssef et al., 2019)	(Adejo & Connolly, 2018; Al-kmali et al., 2020; Huang et al., 2020; Md Rifatul Islam et al., 2019; Pang et al., 2017;	(Adejo & Connolly, 2018; Huang et al., 2020; Monllaó Olivé et al., 2020; Philippou et al., 2020; Sani et al., 2020)	(Huang et al., 2020; Md Rifatul Islam et al., 2019; Philippou et al., 2020; Quan et al., 2019; Tenpipat & Akkarajitsakul, 2020)	(Chen et al., 2020; Philippou et al., 2020)	(Hutagaol & Suharjito, 2019; Md Rifatul Islam et al., 2019; Philippou et al., 2020; Youssef et al., 2019)	(Borrella et al., 2019; Chen et al., 2020; Choi et al., 2018; Huang et al., 2020; Philippou et al., 2020; Quan et al., 2019;	(Choi et al., 2018)		(Iatrellis et al., 2021)			

	Vinuesa, 2019; Huang et al., 2020; Hutagaol & Suharjito, 2019; Iatrellis et al., 2021; Md Rifatul Islam et al., 2019; Philippou et al., 2020; Quan et al., 2019; Sani et al., 2020; Singh & Kaur, 2016; Tenpipat & Akkarajitsakul, 2020; Youssef et al., 2019)		Quan et al., 2019; Youssef et al., 2019)					Youssef et al., 2019)						
Sensitivity (Recall/TP rate)	(Adejo & Connolly, 2018; Aderibigbe & Noma-Osaghae, 2019; Al-kmali et al., 2020; Ashraf et al., 2018; Baneres et al., 2019; Borrella et al., 2019; Chen et al., 2020; Delen, 2010; Delen, 2011; Figueroa-Cañas & Sancho-Vinuesa, 2019; Freitas et al., 2020; Gray & Perkins, 2019; Hoffait &	(Aderibigbe & Noma-Osaghae, 2019; Al-kmali et al., 2020; Baneres et al., 2019; Gray & Perkins, 2019; Huang et al., 2020; Hutagaol & Suharjito, 2019; Palacios et al., 2021; Philippou et al., 2020; Raza et al., 2020; Youssef et al., 2019)	(Adejo & Connolly, 2018; Al-kmali et al., 2020; Baneres et al., 2019; Chui et al., 2020; Ciolacu et al., 2019; Delen, 2010; Freitas et al., 2020; Huang et al., 2020; Liao et al., 2019; Md Rifatul Islam et al., 2019; Palacios et al., 2021; Pang et	(Adejo & Connolly, 2018; Aderibigbe & Noma-Osaghae, 2019; Ciolacu et al., 2019; Delen, 2010; Delen, 2011; Freitas et al., 2020; Gray & Perkins, 2019; Hoffait & Schyns, 2017; Huang et al., 2020; Monllaó Olivé et al.,	(Aderibigbe & Noma-Osaghae, 2019; Huang et al., 2020; Martins et al., 2017; Md Rifatul Islam et al., 2019; Philippou et al., 2020; Quan et al., 2019; Tenpipat & Akkarajitsakul, 2020)	(Chen et al., 2020; Delen, 2010; Philippou et al., 2020)	(Baneres et al., 2019; Freitas et al., 2020; Hutagaol & Suharjito, 2019; Md Rifatul Islam et al., 2019; Palacios et al., 2021; Philippou et al., 2020; Raza et al., 2020; Youssef et al., 2019)	(Aderibigbe & Noma-Osaghae, 2019; Borrella et al., 2019; Chen et al., 2020; Choi et al., 2018; Delen, 2010; Delen, 2011; Freitas et al., 2020; Hoffait & Schyns, 2017; Huang et al., 2020; Palacios et al., 2021; Philippou et al., 2020; Quan et al.,	(Aderibigbe & Noma-Osaghae, 2019; Choi et al., 2018)	(Aderibigbe & Noma-Osaghae, 2019)	(Iatrellis et al., 2021)			

	Schyns, 2017; Huang et al., 2020; Hutagaol & Suharjito, 2019; Iatrellis et al., 2021; Martins et al., 2017; Md Rifatul Islam et al., 2019; Palacios et al., 2021; Philippou et al., 2020; Quan et al., 2019; Raza et al., 2020; Sani et al., 2020; Singh & Kaur, 2016; Tenpipat & Akkarajitsakul, 2020; Youssef et al., 2019)		al., 2017; Quan et al., 2019; Raza et al., 2020; Youssef et al., 2019)	2020; Philippou et al., 2020; Raza et al., 2020; Sani et al., 2020)				2019; Ran et al., 2018; Raza et al., 2020; Youssef et al., 2019)						
Specificity (TN rate)	(Aderibigbe & Noma-Osaghae, 2019; Ashraf et al., 2018; Baneres et al., 2019; Delen, 2011; Martins et al., 2017; Md Rifatul Islam et al., 2019; Palacios et al., 2021; Raza et al., 2020)	(Aderibigbe & Noma-Osaghae, 2019; Baneres et al., 2019; Baranyi et al., 2019; Palacios et al., 2021; Raza et al., 2020)	(Baneres et al., 2019; Chui et al., 2020; Ciolacu et al., 2019; Liao et al., 2019; Md Rifatul Islam et al., 2019; Palacios et al., 2021; Raza et al., 2020)	(Aderibigbe & Noma-Osaghae, 2019; Ciolacu et al., 2019; Delen, 2011; Raza et al., 2020)	(Aderibigbe & Noma-Osaghae, 2019; Martins et al., 2017; Md Rifatul Islam et al., 2019)		(Baneres et al., 2019; Md Rifatul Islam et al., 2019; Palacios et al., 2021; Raza et al., 2020)	(Aderibigbe & Noma-Osaghae, 2019; Delen, 2011; Palacios et al., 2021; Raza et al., 2020)	(Aderibigbe & Noma-Osaghae, 2019)	(Aderibigbe & Noma-Osaghae, 2019)				
F-Measure	(Adejo & Connolly, 2018; Al-kmali et al., 2020; Baneres et al.,	(Al-kmali et al., 2020; Baneres et al., 2019; Gray &	(Adejo & Connolly, 2018; Al-kmali et al., 2020;	(Adejo & Connolly, 2018; Freitas et al., 2020;	(Huang et al., 2020; Philippou et al., 2020; Tenpipat &	(Chen et al., 2020; Philippou et al., 2020)	(Baneres et al., 2019; Freitas et al., 2020; Hutagaol &	(Chen et al., 2020; Freitas et al., 2020; Huang et			(Romero et al., 2013)		(Romero et al., 2013)	

	2019; Chen et al., 2020; Freitas et al., 2020; Gray & Perkins, 2019; Huang et al., 2020; Hussain et al., 2019; Hutagaol & Suharjito, 2019; Palacios et al., 2021; Philippou et al., 2020; Raza et al., 2020; Romero et al., 2013; Sani et al., 2020; Tenpipat & Akkarajitsakul, 2020)	Perkins, 2019; Huang et al., 2020; Hussain et al., 2019; Hutagaol & Suharjito, 2019; Palacios et al., 2021; Philippou et al., 2020; Raza et al., 2020; Romero et al., 2013)	Baneres et al., 2019; Freitas et al., 2020; Huang et al., 2020; Hussain et al., 2019; Palacios et al., 2021; Raza et al., 2020; Romero et al., 2013)	Gray & Perkins, 2019; Huang et al., 2020; Hussain et al., 2019; Monllaó Olivé et al., 2020; Philippou et al., 2020; Raza et al., 2020; Romero et al., 2013; Sani et al., 2020)	Akkarajitsakul, 2020)		Suharjito, 2019; Palacios et al., 2021; Philippou et al., 2020; Raza et al., 2020; Romero et al., 2013)	al., 2020; Hussain et al., 2019; Palacios et al., 2021; Philippou et al., 2020; Raza et al., 2020)						
Correctly Classified		(Trstenjak & Đonko, 2014)	(Trstenjak & Đonko, 2014)											
Incorrectly Classified		(Trstenjak & Đonko, 2014)	(Trstenjak & Đonko, 2014)											
ROC Curve	(Hussain et al., 2019; Naseem et al., 2019; Viloria et al., 2019; Youssef et al., 2019)	(Hussain et al., 2019; Viloria et al., 2019; Youssef et al., 2019)	(Hussain et al., 2019; Liao et al., 2019; Youssef et al., 2019)	(Chen & Cui, 2020; Hussain et al., 2019; Iyanda et al., 2018; Kiss et al., 2019; Monllaó Olivé et al., 2020; Viloria et al., 2019)	(Kiss et al., 2019)		(Youssef et al., 2019)	(Hussain et al., 2019; Sajjadi et al., 2017; Youssef et al., 2019)			(Sajjadi et al., 2017)			
AUC	(Gray & Perkins, 2019; Huang et al., 2020; Hussain et al., 2019;	(Gray & Perkins, 2019; Huang et al., 2020;	(Huang et al., 2020; Hussain et al., 2019;	(Baranyi et al., 2020; Chen & Cui, 2020; Gray & Perkins,	(Baranyi et al., 2020; Huang et al., 2020; Mngadi et al., 2020; Nagy &			(Huang et al., 2020; Hussain et al., 2019; Mngadi et	(Nagy & Molontay, 2018)		(Iatrellis et al., 2021)			

	Iatrellis et al., 2021; Mngadi et al., 2020; Nagy & Molontay, 2018; Zabriskie et al., 2019)	Hussain et al., 2019)	Mngadi et al., 2020)	2019; Huang et al., 2020; Hussain et al., 2019; Nagy & Molontay, 2018)	Molontay, 2018)			al., 2020; Nagy & Molontay, 2018; Zabriskie et al., 2019)						
SSE											(Marbouti et al., 2020)			
RMSE	(Adejo & Connolly, 2018; Allah, 2020; Hussain et al., 2019; Lye et al., 2010; Palacios et al., 2021)	(Hussain et al., 2019; Palacios et al., 2021; Trstenjak & Đonko, 2014)	(Adejo & Connolly, 2018; Hussain et al., 2019; Palacios et al., 2021; Trstenjak & Đonko, 2014)	(Adejo & Connolly, 2018; Hussain et al., 2019; Lye et al., 2010)	(Allah, 2020; Wham, 2017)		(Palacios et al., 2021)	(Hussain et al., 2019; Palacios et al., 2021)		(Alshanqiti & Namoun, 2020)			(Iqbal et al., 2019; Jembere et al., 2017)	(Iqbal et al., 2019)
MAE		(Philippou et al., 2020; Trstenjak & Đonko, 2014)	(Trstenjak & Đonko, 2014)	(Philippou et al., 2020)	(Philippou et al., 2020)	(Philippou et al., 2020)	(Philippou et al., 2020)	(Philippou et al., 2020)					(Iqbal et al., 2019)	(Iqbal et al., 2019)
MSE	(Wakelam et al., 2020)			(Chanamarn & Tamee, 2017; Iyanda et al., 2018)			(Wakelam et al., 2020)				(Chanamarn & Tamee, 2017)			
KAPPA	(Hussain et al., 2019; Md Rifatul Islam et al., 2019; Mngadi et al., 2020; Naseem et al., 2019)	(Hussain et al., 2019; Trstenjak & Đonko, 2014)	(Hussain et al., 2019; Md Rifatul Islam et al., 2019; Mngadi et al., 2020; Trstenjak & Đonko, 2014)	(Hussain et al., 2019)	(Md Rifatul Islam et al., 2019; Mngadi et al., 2020)		(Md Rifatul Islam et al., 2019)	(Hussain et al., 2019)	(Mngadi et al., 2020)					
Unspecified	(Tsiakmaki et al., 2018)		(Tsiakmaki et al., 2018)		(Tsiakmaki et al., 2018)		(Tsiakmaki et al., 2018)		(Sravani & Bala, 2020; Tsiakmaki		(Biradar, 2015)	(Trandafili et al., 2012)	(Mai et al., 2019)	(Mai et al., 2019; Trandafili

										et al., 2018)						et al., 2012)
Confusion Matrix	True Positive False Negative False Positive True Negative	(Adekitan & Salau, 2019; Ajoodha et al., 2020; Berens et al., 2019; Berriri et al., 2021; Buenaño-Fernández et al., 2019; Gray & Perkins, 2019; Gray et al., 2016; Mimis et al., 2019; Mngadi et al., 2020; Ndou et al., 2020; Ramaswami et al., 2019; Segura-Morales & Loza-Aguirre, 2018; Tenpipat & Akkarajitsakul, 2020; Yang et al., 2020)	(Adekitan & Salau, 2019; Ajoodha et al., 2020; Gamie, El-Seoud, et al., 2019; Gray & Perkins, 2019; Gray et al., 2016; Mimis et al., 2019; Ndou et al., 2020; Ramaswami et al., 2019)	(Ajoodha et al., 2020; Gray et al., 2016; Mngadi et al., 2020; Ndou et al., 2020)	(Adekitan & Salau, 2019; Berens et al., 2019; Gray & Perkins, 2019; Gray et al., 2016; Mimis et al., 2019)	(Berens et al., 2019; Mngadi et al., 2020; Segura-Morales & Loza-Aguirre, 2018; Tenpipat & Akkarajitsakul, 2020)		(Gray et al., 2016; Ramaswami et al., 2019)	(Adekitan & Salau, 2019; Ajoodha et al., 2020; Berens et al., 2019; Gray et al., 2016; Ndou et al., 2020; Ramaswami et al., 2019)	(Mngadi et al., 2020)					
Evaluation metrics / **Algorithms**		Decision trees	Bayesian algorithms	Support Vector Machine	Neural Networks	Boosting Algorithm	Bagging Algorithm	K-Nearest Neighbor	Logistic Regression	Linear Regression	Polynomial Regression	K Mean	Association rule	Matrix Factorization	NonNegative Matrix Factorization

Table 6: Different ML algorithms vs evaluation metrics

In terms of evaluation metrics, Accuracy (49%) is most frequently used to measure the performance of the model, followed by the Sensitivity(aka Recall or True Positive rate – 37%), Precision (21%), F-measure (17%) and Specificity (aka True Negative rate – 12%) Other performance metrics are also used for evaluation in the reviewed studies e.g. root mean square error (RMSE), mean absolute error (MAE) as given in Table 6. Few studies (6%) did not specify the evaluation measuring metric of the ML model.

To conduct a quantitative comparison of the results with the related studies, althrough it was relatively complicated due to the fact of different dataset and variation in strategies of literature collection, presented result show higher potertials over other works. For example, in [10], data mining was used for capturing on student performance, in [11], deep learning used for historical data trends and opportunities and in [13] audience response system used for capturing of student experience. In comparison, our results are based on a holistic meta-analysis including on student academic performance, at-risk, and attrition in the higher education domain.

Most of the selected studies have performed well with high accuracy of ML algorithms to predict student progress. Accuracy is often used to evaluate the performance of a classification and supervised model, therefore, figure 13 shows the distribution of the highest accuracy percentage of classifiers in the selected studies. Only the highest accuracy is selected as the outcome of the study regardless of the different investigations performed in the study.

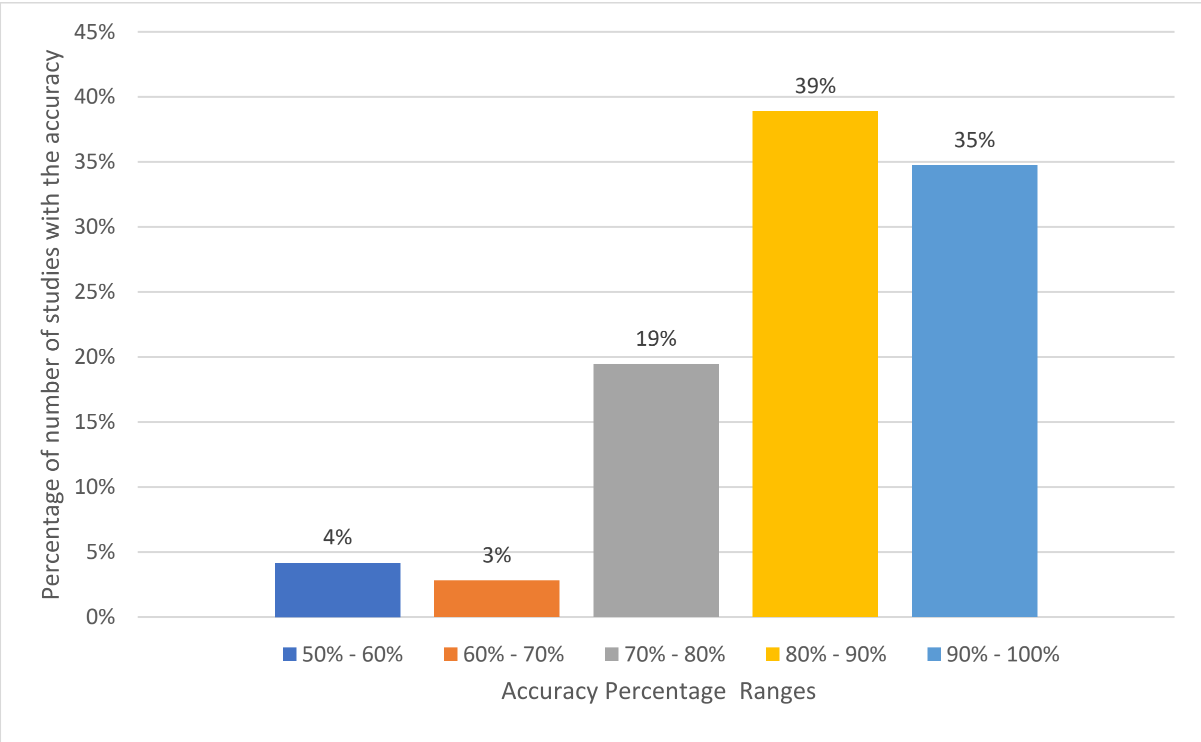

Figure 13: Distribution of the highest accuracy percentage in the selected studies

Future directions are mentioned in most of the selected studies. Following is the summary of the recommendation made as to future research direction in the reviewed studies. The leading focus is to extend the existing study to

- Investigate the adoption and application of the more recent ML algorithms
- Investigate by utilizing Deep learning techniques
- Evaluate the changes by applying the latest ensemble models
- Analyse models accuracy changes with augmented data (increased instances)
- Investigate the variation of the accuracy of the model with an enhanced features dataset
- Assess the performance by application of feature selection techniques and selection of different feature selection from the dataset
- Investigate the use of a similar dataset with the same features retrieved from different educational settings
- Assess the outcome of the application of the model on the real dataset

5. Overall discussion and Conclusion

The main aim of this review study is to further understand the trends of the application of ML in HE. The paper presented a systematic literature review of studies by using the PRISMA framework. The 89 studies were selected based on search protocol including inclusion and exclusion criteria and research questions are formulated to set the focus of the research, highlighted the demographic knowledge of the selected studies, and identified the ML algorithms with evaluation metrics used in the studies. In the existing literature, limited review studies have outlined a comprehensive overview of the application of ML in the HE sector towards a positive impact on student academic performance, at-risk, and attrition. Thus, this systematic review study contributed to educational technology literature by providing rich findings. Following our restricted selection protocol, only a limited set of studies from literature could be included in this research that formed the main limitation of the systematic review and meta-analyses conducted in this work. In the future, researchers may consider expanding the search databases, publication types, or languages to enhance the scope of the systematic review.

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