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Students' Performance Predictive Models on OULAD Dataset: A Brief Review

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ABSTRACT

This review introduces a brief summary of the studies in the scope of student performance predictive models implemented on the OULAD dataset. These works are grouped based on the publish year for the last three years. After that, it gives a brief overview of the techniques used in predictive models, types of classification applied, chosen time for prediction, selected features used, and evaluation metrics. The summary of the OULAD predictive models is also presented in this review.First finding of this review is that, because the OULAD dataset is a time series data there is a need to more studies focusing on predicting student performance in the early stages of the course to help instructor making suitable in time intervention. Second, few studies make a multi classification predictive models due to the difficulties to recognise minority classes (Distinct and Fail) and Imbalanced distribution of student performance.Finally, the trendis to use deep learning techniques because deep learning techniques discover the latent dependencies between features and the target variable and no need to features extraction stage to discover the students' performance on the OULAD dataset.

Keywords:OULAD dataset, Learning Analytics, Student Performance Prediction, Deep Learning, Machine Learning, MOOC

INTRODUCTION

Nowadays there is an exponential increase of web-based educational systems. These systems generate large repositories of educational data including high educational value information. There is a big need to transform this generated educational data to new insights that can be useful for students, teachers, and administrators. For this purpose, different communities have grown. One of them is Learning Analytics(Romero and Ventura 2020).

Learning analytics (LA) "refers to the use of intelligent data, learner-produced data, and analysis models to discover information and social connections, and to predict and advise on learning(Ranjeeth, Latchoumi, and Paul 2020).Educational data used in LA supports learning, teaching, and administration(Daniel 2017). As a teaching process the outcome of LA can help identifying at-risk students, improving teaching and getting instant feedback.

In the recent ten years, Research that predicts student performance has increased significantly and uses different techniques(Petersen, Ajanovski, and Messom n.d.). Most research used statistical methods such as linear modelling and correlations methods to predict student performance. As deep learning (DL) methods considered the state of the art of machine learning (ML),

many research applied some deep learning methods to predict the final performance of students(Petersen, Ajanovski, and Messom n.d.).

The value being predicted as student performance is varied based on the objective of prediction(Petersen, Ajanovski, and Messom n.d.). Authors in (He et al. 2020) and (Aljohani, Fayoumi, and Hassan 2019) deploy deep learning models to identify students at-risk of failing in a course so; instructors can make a suitable intervention to support such students. In [9] authors proposed a deep learning model to predict withdrawal students from massive open online courses (MOOC). They aimed to facilitate the academia and administration formulating strategies which enabled student retention. This review introduces a brief review of student performance predictive models implemented on the OULAD dataset. The predictive models are grouped based on the publish year into 2022, 2021, 2020, and 2019.Then it, gives a brief overview of the techniques used, types of classification applied, prediction time, selected features, and evaluation metrics.

The rest of this review is organized as follows: section 2 introduces the method of this study. Section 3discuss the predictive models on the OULAD dataset. Finally, section 5 illustrates thesis outline.

Method

This paper summarizes the students' performance predictive models which applied on the OULAD dataset. To accomplish this task, Google Scholar search engine has been searched. The search keys were like "predict student performance oulad deep learning", "predict student outcomes OULAD" "student performance prediction "," open university learning analytics dataset prediction". The results obtained between 2022 and 2019 was 445,in march 2022. Unrelated articles were ruled out. Also, unindexed Conferences and journals, and non-English articles were excluded. Only ranked journal articles in SCImago Journal Rank (SJR) (https://www.scimagojr.com) were included. The articles varied between predictive models on OULAD dataset, comparative studies between different machine learning algorithms, and systematic literature reviews and surveys. The remaining 14 articles predictive models on OULAD were analysed and included in this review. The aim of this review is to summarize what are deep learning and machine learning algorithms implemented on OULAD data set to predict student performance.

The OULAD Dataset Description

Open University Learning Analytics Dataset is one of a public Learning Analytics dataset,cited by more than 266 articles, containing data for 32,593 students studied in open online courses [3]. This data collected from the Open University, one of the largest distance learning institutions in United Kingdom(Hlioui, Aloui, and Gargouri 2021).The OULAD dataset contains demographic, assessment, course and click stream interaction data. Seven online courses offered in four different semesters for students from different education levels and ages. Each interaction "click" on any activity in a virtual learning environment was recorded in a separate table called "StudentVle". The OULAD data set is available in (https://analyse.kmi.open.ac.uk/open_dataset) and (https://www.kaggle.com/anlgrbz/student-demographics-online-education-dataoulad) Table I describes the OULAD dataset.

Table IThe OULAD Dataset Description

Years	2013,2014
Courses	7 courses
Number of courses introduced	22
Min – max course period	234-269 days
No. of unique students	28785
No. of students in all courses	32593
No. of assessments	206
No. of activities	6364

predictive models on The OULAD dataset

Recently in 2022,Authors in (Qiu et al. 2022) proposed a prediction framework based on six traditional machine learning algorithms (SVC (R), SVC (L), Naïve Bayes(NB), K-Nearest Neighbour (KNN) and sofmax) .The expected output value of the predictor was" qualified" or" unqualified". Authors in (Qiu et al. 2022) used "DDD" course with click stream data in 12 activities.In (Hao, Gan, and Zhu 2022) researchers developed a Bayesian Network(BN) base prediction model for final performance and compared it with Gradient Boosting(GB) Decision Tree, Multi-Layer Perception (MLP) and Naïve Bayesian Network(NB) ensemble

models. The value of calculated performance was divided, according in the students' scores in assessments, into fail, pass, good, and distinction.As a multiclass classification model (Adnan et al. 2022) developed different ML models to predict student performance with the four classes Distinct, pass, fail, and withdrawn. The compared models was Random Forest with two different criterion 'gini'and 'entropy', 'AdaBoost', Extra Tree classifier, KNN, Decision Tree (DT), Support Vector Machine (SVM), Gradient Boosting, Logistic Regression (LR), Gaussian Naïve Bayes, Bernoulli Naïve Bayes classifier, and only one DL classifier (Feed Forward Neural Network (FFNN)).

Earlier in 2021,(Adnan et al. 2021) used Deep Feed Forward Neural Network to predict a student's final result (distinct pass withdrawn fail) with best average accuracy obtained at the last time of courses was 43%when input data was demographic data, 63%when input data was demographic and click steam, 71% when input data was demographic, click steam and assessment and 72% when input data was all features available in OULAD dataset .In Addition, multi classification was converted to binary classification so that distinction and pass class were combined into pass class and fail and withdrawn were combined into fail class. After this converting the accuracy obtained was 90% at the end of courses. Authors of (Adnan et al. 2021)did not mention the accuracy obtained at early stages of courses.Another research was published is (Pei and Xing 2021). It used demographic and aggregated clickstream data of two social sciences (AAA_2013J and AAA_2014J) and two Science, Technology, Engineering and Mathematics (STEM) courses(CCC_2014B and CCC_2014J) as input. It developed a supervised machine learning model with expectation maximum algorithm to predict whether a student will stay or drop out in previous week then used the resulted probability as input to improve prediction accuracy for the current week.The OULAD dataset is imbalanced. So, authors in (Pei and Xing 2021)used Synthetic Minority Over-Sampling (SMOTE) technique. The average accuracy obtained for selected courses in all weeks was Approximately 88%.Authors of (Vo and Nguyen 2021)proposed a semi-supervised learning ensemble model of Artificial neural network (ANN) to predict student performance (pass or fail) before midterm and at the end of course .Five specific courses of OULAD data set were chosen as input to the proposed model. Each chosen course was available in two different semesters. The first course used for training while the second used for testing. The average accuracy obtained for selected courses was 87.47% at the middle of semester. Authors in(Vo and Nguyen 2021) ignored distinction and withdrawal students data which represents around 40% of OULAD dataset. Prediction limited to the trained course. As (Pei and Xing 2021), (Hlioui, Aloui, and Gargouri 2021) predicted withdrawal students with different models (Decision tree(J48), Random Forest, Bayesian classifier (TAN), SVM classifier, and MLP) classifiers using clickstream, assessment, and demographic data. Student performance was divided into two values: withdrawal and completion ("Distinction" or "Pass" or "Fail").The importance of assignment information for students' performance prediction was explored in (Esteban and Romero 2021).It developed Multiple Instance Learning predictive model to predict passed and failed students. Features used was assessment data. Finally, (Kumar Verma, Srivastava, and Kumar Singh 2021)compared the performance of Classification Algorithms (NB, RF, k-NN SVM, and ANN) in predicting final exam grades. Assessment, Demographic, and Clickstream data was used as input of the prediction model. previously in 2020, (He et al. 2020)ignored the 'withdrawal' students data and proposed Recurrent Neural Network(RNN)- Gated Recurrent Unit(GRU) joint neural network to predict whether student will fail or pass (merged 'distinction' and 'pass' labels into 'pass') using demographic , clickstream, and assessment data. The prediction was at course level. So, the last courses were used as test set. The averaged accuracy obtained in all courses was between 60-90% from 5th week till the 39th week.Authors of (Waheed et al. 2019)treated the final result as a binary classification and deployed four deep ANN models to predict fail, withdrawn, ,and distinct students using demographic and click stream data. Authors of (Waheed et al. 2019)used sparse reduction to select 30 features over total of 54 features and used "MinMax" scaler to transform The values of the selected features. The prediction was performed in four quarters of semester. The accuracy obtained in fail prediction model was around 77%,81%,86% and 88% in quarter1, quarter2, quarter3, and quarter4 respectively. In the fail prediction model withdrawal student's data was ignored and distinction merged with passed data. The accuracy

obtained in the withdrawn prediction model was around 78%,86%,90% and 93% in quarter 1, quarter 2, quarter 3, and quarter 4 respectively. In the withdrawn prediction model fail student's data was ignored and distinction merged with passed data. The accuracy obtained in the two distinction prediction models was between 80- 81% when withdrawn and fail data was ignored and between 80-85% when withdrawn and pass data was ignored.

Three years ago in 2019 ,(Hassan et al. 2019)used click data to predict withdrawn students every five weeks to week 25 with Long Short-Term Memory (LSTM) deep model. Withdrawn data was ignored in (Hassan et al. 2019). The accuracy obtained in 5th week was around 80% and in the 25th week was around 97%.(Wasif et al. 2019)proposed different machine and deep learning models (Random Forest (RF), Multiple Layered Perceptron with multiple activation functions , and Gaussian Naïve Bayes)to predict student performance pass and fail using demographic information, click stream data ,generated features , and Total Features.Authors Merged withdrawn and fail students in fail class and Merged distinguish and Pass in Pass class.

Table IIcompares the studies on the OULAD predictive models in terms of the following perspectives:

1. The type of the classification based on the output of the predictive model (binary classification or multiclass classification).
2. The outcome of the prediction process (pass/fail, withdrawn/not withdrawn, Withdrawn /Fail /Pass/ Distinction, ...).
3. The time of prediction process (at the end of course, weekly, quarterly, ...).
4. Features used as input of the models (demographic data, clickstream data, assessment data, ….).
5. The methods implemented in the model (support vector machine,artificial neural network, long short term memory, …).

Table IIComparison of the predictive models on the OULAD dataset

Ref	Type	Outcome	Time	Features	Methods	Comment
(Qiu et al. 2022)	binary	Qualified Unqualified	Final	Clickstreams in 12 activities for students belong to "DDD" course	SVC , (L), NB, KNN , softmax	Course level prediction limited to a specific course
(Hao, Gan, and Zhu 2022)	multi	Fail Pass Good Distinction	Final	Demographic register duration, the sum of clicks, and the average scores of the intermediate tests	BN	Calculated Classes depend on assessments score not the final result in the OULAD
(Adnan et al. 2022)	multi	Withdrawn Fail Pass Distinction	Final	All features	RF AdaBoost Extra Tree KNN DT	Not a time series

					SVM, Gradient Boosting, LR, NB (FFNN)	
(Adnan et al. 2021)	multi	Withdrawn Fail Pass Distinction	final	All features	DFFNN RF SVM K-NN ET AdaBoost Gradient boosting ANN	Discussed only Final accuracy of the predictive model
(Pei and Xing 2021)	binary	dropout (withdrawn) or not	weekly	Demographic and Click stream data for students belong to (AAA_2013J AAA_2014J CCC_2014B CCC_2014J) courses	ML RF SVM DT	Course level prediction limited to a specific courses
(Vo and Nguyen 2021)	binary	Pass /fail	med term and final	Assessment features of students belong to (AAA, BBB, CCC, DDD, and FFF) courses	Semi supervised ANN C4.5 k-NN Logistic NB RF SVM	Course level prediction limited to specific courses Excludes Withdrawal and Distinction
(Hlioui, Aloui, and Gargouri 2021)	binary	withdrawal /completion	final	Assessment Demographic Clickstream	J48,RF SVM ANN BN	
(Esteban and Romero 2021)	binary	Pass/fail	final	assessment	Multiple Instance Learning	
(Kumar Verma,	binary	Pass/fail	final	Assessment Demographic	NB RF	Prediction for final

Srivastava, and Kumar Singh 2021)				Clickstream	k-NN SVM ANN	exam score
(He et al. 2020)	binary	Pass/fail	Week wise	Demographic Assessment click stream	RNN GRU	Ignore withdrawal student (represents 31% of the data set)
(Waheed et al. 2019)	binary	Pass/Fail Distinct/Pass Distinct/Fail Withdrawn/Pass	Four Quarter	Demographic click stream and click stream only	ANN	Merge distinguish and Pass
(Aljohani, Fayoumi, and Hassan 2019)	binary	Pass/fail	Week wise	click stream	LSTM	Ignore withdrawal student Ignore repeated course
(Hassan et al. 2019)	binary	Withdrawn/Pass	Week wise	click stream	LSTM	Ignore fail and distinction
(Wasif et al. 2019)	binary	Pass/fail	-	All	Machine learning	Merge withdrawn and fail Merge distinguish and Pass

Evaluation Metrics Used

Most studies used accuracy,precision,recall, and F1-score as evaluation metrics.(Pei and Xing 2021)The AUC was used in (Vo and Nguyen 2021) and (Pei and Xing 2021) to assess the performance of machine learning models because the dataset is imbalanced. Accuracy , recall, and precision were used in (Adnan et al. 2021), (Pei and Xing 2021), [3], (He et al. 2020), (Waheed et al. 2019), and (Hassan et al. 2019).F1- score measure were used in(Adnan et al. 2021), (Pei and Xing 2021), and [3]. loss evaluation were used in (Waheed et al. 2019) and (Hassan et al. 2019)(Adnan et al. 2021)used support evaluation metric. Table III shows the evaluation metrics used in the reviewed works. Figure I shows the frequency of The evaluation metrics used in the OULAD predictive models

Table IIIEvaluation Metrics Used in The Related Works

ref	accuracy	recall	precision	f1-score	loss	AUC	ROC	j index	Kappa	support
(Qiu et al. 2022)	✓			✓					✓ *	
(Hao, Gan, and Zhu 2022)		✓	✓	✓						
(Adnan et al. 2022)	✓	✓	✓	✓						
(Adnan et al. 2021)	✓	✓	✓	✓						✓
(Pei and Xing 2021)	✓	✓	✓	✓		✓				
[3]	✓	✓	✓	✓		✓				
(Hlioui, Aloui, and Gargouri 2021)				✓						
(Esteban and Romero 2021)	✓	✓	✓							
(Kumar Verma, Srivastava, and Kumar Singh 2021)	✓			✓				✓		
(He et al. 2020)	✓	✓	✓							
(Waheed et al. 2019)	✓	✓	✓		✓					
(Hassan et al. 2019)	✓	✓	✓		✓					
(Wasif et al. 2019)		✓	✓	✓			✓			

Machine Learning and Deep Learning Techniques Used on The OULAD Dataset

DL techniques structure algorithms in layers that can learn and make sensible judgments on their own and that is the core difference from the techniques used in traditional ML algorithms(Adnan et al. 2021). DL algorithms process data by using graphs of neurons in different layers known as input, hidden, and output layers.

The predictive models research distributed mostly equal in using deep learning and machine learning techniques. Table IV shows the distribution of the predictive modelson deep and machine learning.Figure II shows number of studies used for each algorithm.

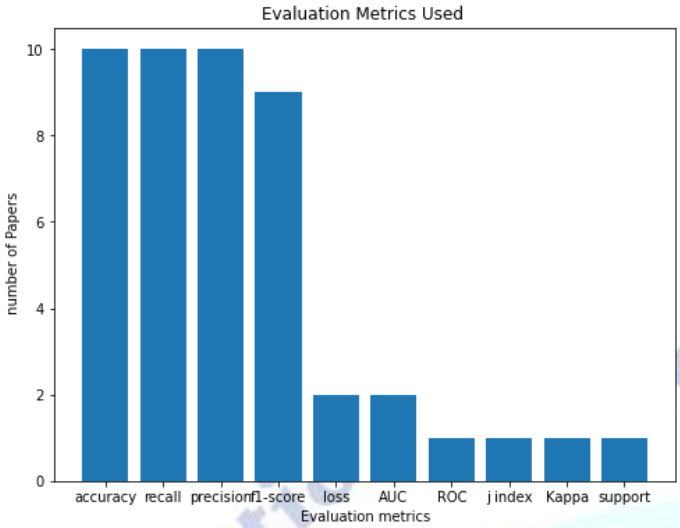

Figure I The Evaluation Metrics Used in The OULAD Predictive Models

Just one research of the related works published in 2022 used deep learning technique which was Feed-Forward Neural Network.(Qiu et al. 2022)used machine learning SVC (R), SVC (L), Naïve Bayes, KNN (U), KNN (D) and softmax. (Hao, Gan, and Zhu 2022) used Bayesian Network technique. And finally,(Adnan et al. 2022)used ML(Decision Tree (DT)) and DL(Feed-Forward Neural Network (FFNN)).

Most of related works published in 2021 used ML and DL techniques. (Adnan et al. 2021)used deep learning technique (Deep Feed Forward Neural Network). (Pei and Xing 2021)constructed a machine learning model. (Vo and Nguyen 2021)used DL technique(ANN) and ML techniques(C4.5, k-NN, Logistic, NB, RF, and SVM). (Hlioui, Aloui, and Gargouri 2021) used DL technique(ANN) and ML techniques (DT(J48,RF), SVM, and Bayesian classifier. (Esteban and Romero 2021) used DL technique(ANN,MLP) and ML techniques (Tree, SVM, Rule and ensemble classifiers). (Kumar Verma, Srivastava, and Kumar Singh 2021) used DL technique(ANN) and ML techniques (NB, RF, k-NN, and SVM).

The two related works published in 2020 used DL techniques. (He et al. 2020) used DL techniques (RNN, and GRU), and (Waheed et al. 2019)used a Deep Artificial Neural Network.

In 2019, (Hassan et al. 2019), and (Aljohani, Fayoumi, and Hassan 2019) used a DL technique (LSTM), and (Wasif et al. 2019)used ML techniques(Gradient Boosting Classifier, Gaussian Naïve Bayes, LinearSVC, Bernoulli Naïve Bayes , DT, RF, and LR). Table IVsummaries The algorithms implemented on the OULAD Predictive Models.

Table VDistribution of studies Based On the Techniques Used

year	reference	DL technique	ML technique
2022	(Qiu et al. 2022)		✓
	(Hao, Gan, and Zhu 2022)		✓
	(Adnan et al. 2022)	✓	✓
2021	(Adnan et al. 2021)	✓	
	(Pei and Xing 2021)		✓
	(Vo and Nguyen 2021)		✓
	(Hlioui, Aloui, and Gargouri 2021)	✓	✓
	(Esteban and Romero 2021)	✓	✓
	(Kumar Verma, Srivastava, and Kumar Singh 2021)	✓	✓
2020	(He et al. 2020)	✓	
	(Waheed et al. 2019)	✓	
2019	(Hassan et al. 2019)	✓	
	(Wasif et al. 2019)	✓	✓

1.1 Classification Types Based on The Prediction Outcome

The research in predicting student performance, which applied on the OULAD dataset, can be divided based on prediction outcome to binary and multi classification. In binary classification the prediction outcome forecasts if a student will fail or pass the current course. Another binary classification predicts if a student will withdraw or continue studying a current course. In multi classification the models figure out the in deep the student performance type (Distinct, Pass, Fail, or Withdrawn)

Binary classification Models

Authors in [7] compared accuracy of GRU, RNN, and LSTM neural network algorithms in identifying students at-risk of failure using demographic, assessment and click stream data discarding all data of withdrawn students and they achieved over 80% accuracy in later days of the course.

A Long Short-Term memory model deployed in [7] to predict failing students dividing data in a week wise manner and using only clickstream data. They ignored student's data for a repeated course and as [7] ignored withdrawal students. The accuracy achieved in [5] ranged between 69.69% in the 1st week and 95.23% in the last week.

Another Long Short-Term memory model proposed in [8] to predict withdrawn and pass students using aggregated clickstream data organized in week wise form.

Research [8] used a deep artificial neural network model to predict student performance dividing the data set to four quarters and used feature reduction techniques to select 30 features from 54 features in the OULAD dataset. Then they manipulated four class categories using four stages of binary classification (pass-fail), (Distinction-pass), (Distinction-fail), and (Withdrawn-Pass) with overall accuracy 88%, -, 85%, 93% respectively.

Table VIML and DLAlgorithms Used inthe Models.

YEAR	REF	ANN	MLP	LSTM	CNN	GRU	RNN	ML	BN
2022	(Qiu et al. 2022)							✓	
	(Hao, Gan, and Zhu 2022)		✓					✓	✓
	(Adnan et al. 2022)		✓						
2021	(Adnan et al. 2021)		✓					✓	
	(Pei and Xing 2021)							✓	
	(Vo and Nguyen 2021)							✓	
	(Hlioui, Aloui, and Gargouri 2021)		✓						
	(Esteban and	✓						✓	

	Romero 2021)								
	(Kumar Verma, Srivastava, and Kumar Singh 2021)	✓			✓			✓	
2020	(He et al. 2020)					✓	✓		
	(Waheed et al. 2019)	✓							
2019	(Hassan et al. 2019)			✓					
	(Wasif et al. 2019)		✓					✓	
	(Aljohani, Fayoumi, and Hassan 2019)			✓					

Multi Classification Models

Few studies proposed a multi classification models on The OULAD.Paper [9] selected three courses of OULAD dataset and built a LSTM model to predict student performance of the similar courses. The predicted performance was divided to Fail, Pass, Good, and Distinctionbased on the students' scores in the course assessments. In[10] and [11]the predicted performance was Withdrawn, Fail, Pass, and Distinction based on the final result proposed in the OULAD. Table VII shows the distribution of the predictive models between binary and multi classification.Figure IIshows the percentage binary and multi classificationpredictive models on The OULAD dataset.

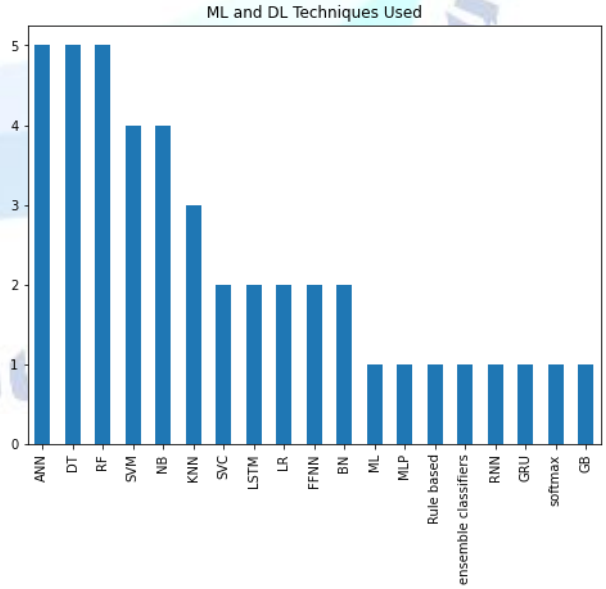

Figure IIIAlgorithms used in the Predictive Models

Sequence Prediction and Final Prediction

Time series (sequence) prediction is used to forecast value at some future time using available observations from a previous time (Han et al. 2021).While the OULAD data has the nature of static and time series, the related works varied. Many studies proposed prediction models to predict student performance at the end of the course and before the final exam. Also, around the half of the proposed models make a timely prediction of students' performance. A weekly prediction model was introduced in (Pei and Xing 2021), (He et al. 2020), (Aljohani, Fayoumi, and Hassan 2019), and (Hassan et al. 2019), While authors in (Adnan et al. 2021) performance prediction model at five different times along the course period. In (Vo and Nguyen 2021) two times for prediction was applied ,in the med and at the end of the course. Finally, (Waheed et al. 2019)applied the prediction quarterly along the course period. Table VIII illistrates the time intervals for predicting students' performance in the related works.Figure IV shows the percentage of the prediction time determined by each OULAD predictive models.

Table IX Classification Types of The OULAD Predictive Models

YEAR	REF	BINARY CLASSIFICATION	MULTI CLASSIFICATION
2022	(Qiu et al. 2022)	✓	
	(Hao, Gan, and Zhu 2022)		✓
	(Adnan et al. 2022)	✓	✓
2021	(Adnan et al. 2021)		✓
	(Pei and Xing 2021)	✓	
	(Vo and Nguyen 2021)	✓	
	(Hlioui, Aloui, and Gargouri 2021)	✓	
	(Esteban and Romero 2021)	✓	
	(Kumar Verma, Srivastava, and Kumar Singh 2021)	✓	
2020	(He et al. 2020)	✓	
	(Waheed et al. 2019)	✓	
2019	(Hassan et al. 2019)	✓	
	(Wasif et al. 2019)	✓	

	(Aljohani, Fayoumi, and Hassan 2019)	✓	

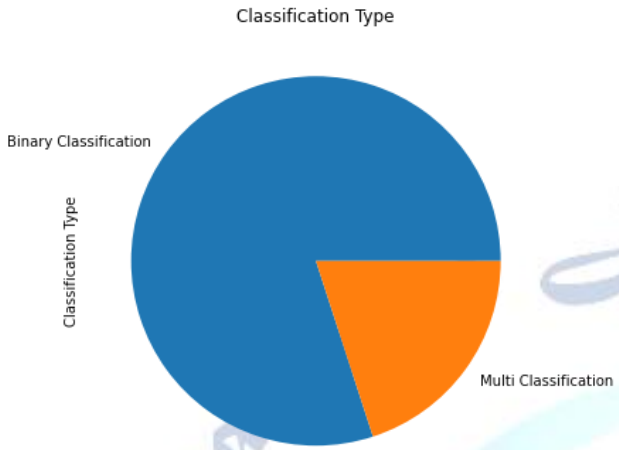

Figure VDistribution of The OULAD Predictive Models Based on The Classification Type

Table XTime Series Intervals in The Related Works

YEAR	REF	SEQUENCE	FINAL
2022	(Qiu et al. 2022)		FINAL
	(Hao, Gan, and Zhu 2022)		FINAL
	(Adnan et al. 2022)		FINAL
2021	(Adnan et al. 2021)	5 TIMES	
	(Pei and Xing 2021)	WEEKLY	
	(Vo and Nguyen 2021)	MED TERM AND FINAL	
	(Hlioui, Aloui, and Gargouri 2021)		FINAL
	(Esteban and Romero 2021)		FINAL
	(Kumar Verma, Srivastava, and Kumar Singh 2021)		FINAL
2020	(He et al. 2020)	WEEKLY	
	(Waheed et al. 2019)	4 QUARTERS	
2019	(Hassan et al. 2019)	WEEKLY	
	(Wasif et al. 2019)		FINAL
	(Aljohani, Fayoumi, and Hassan 2019)	WEEKLY	

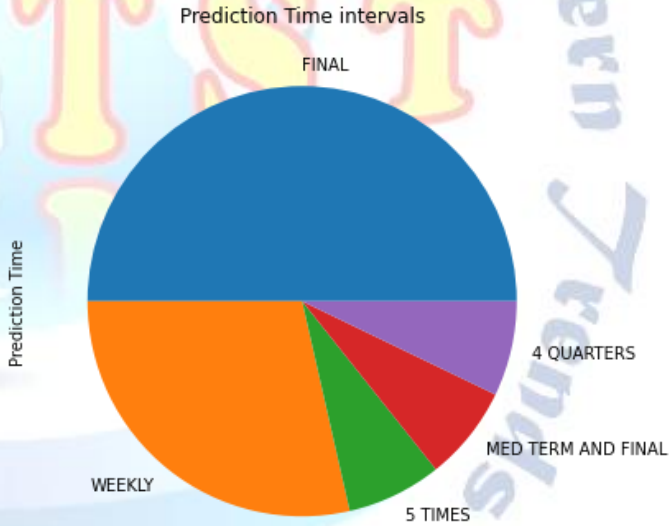

Figure VIThe Prediction Time Determined by The OULAD Predictive Models

CONCLUSIONS

This review presents a summary of machine learning and deep learning predictive models applied on the OULAD for classifying the student performance. The reviewgets several conclusions. First,although The nature of data in the OULAD dataset is mostly time series data, most research apply prediction at the end of the course period. So, there is a need to more studies focusing on predicting student performance in the early stages of the

course to help instructor making suitable in time intervention. Second, few studies make a multi classification predictive models due to the difficulties to recognise minority classes (Distinct and Fail) and Imbalanced distribution of student performance. Third,the trends on techniques used to discover the students' performance on the OULAD dataset is deep learning techniques this may because deep learning techniques discover the latent dependencies between features and the target variable and no need to features extraction stage

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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