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PAPER

Convolutional Neural Network and GridSearch for Predicting Learner Performance in E-Learning

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ABSTRACT

Predicting student performance earlier is among the most significant research areas in e-learning. Accurate prediction allows educators and stakeholders to take the appropriate precautions and make decisions ahead of time to enhance learning outcomes. Numerous previous studies have employed conventional machine learning processes. This work investigated the effectiveness of a convolutional neural network (CNN) to predict learner performance in a virtual learning environment (VLE). This STUDY employed three independent feature selection methods: 1) CNN, 2) random forest (RF), and 3) autoencoder (AE). The GridSearch cross validation (GridSearchCV) strategy explored crucial model hyperparameters that optimize performance. This paper uses the Open University learning analytics dataset (OULAD), which contains data from 32,593 learners enrolled in 22 courses offered by the Open University. The synthetic minority oversampling technique (SMOTE) resolved the issue of an imbalanced dataset. Stratified cross-validation splits the data into training, validation, and testing sets. The proposed approach reached an accuracy of 88% in multi-class classification and 94% in binary classification, outperforming all previous studies that utilized Open University learning analytics dataset.

KEYWORDS

virtual learning environment (VLE), autoencoder (AE), feature selection, synthetic minority oversampling technique (SMOTE), random forest (RF), stratified cross-validation

1 INTRODUCTION

E-learning [1] has advanced notably in the near past, especially amid the COVID-19 pandemic. It serves as an alternative avenue for skill acquisition. Numerous studies have indicated a decline in learner performance during this period [2], [3]. Some learners experienced difficulties achieving adequate scores, while others withdrew from their virtual learning environment (VLE) [4]. The absence of direct contact and lack of motivation are significant contributing factors.

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Predicting student performance in e-learning is crucial for intervening at the right moments and taking the most effective precautions and decisions. This intervention improves learner performance and provides each learner with a pedagogical experience tailored to their needs. Numerous studies in the last few years have concentrated on this domain, employing artificial intelligence (AI) [5]. Machine learning (ML) [6], as a subset of AI, frequently addresses the issue. The core tenet involves supplying a machine with data and allowing it to acquire knowledge without explicit programming to generate predictions.

Various approaches have been employed: Daud et al. [7] utilized support vector machines (SVM), classification and regression trees (CART), Bayesian networks (BN), and Naive Bayes classifiers (NB) to separate students who can graduate from those who cannot. They obtained an F1-score of 86% with the SVM model. The study examined two new feature sets called family expenditures and learner personal information. Alija et al. [8] exploited many supervised ML methods to identify students who encountered problems understanding the course material. The synthetic minority oversampling technique (SMOTE) tackled the issue of imbalanced datasets. Particle swarm optimization determined the most effective features for classification. The random forest (RF) model achieved noteworthy performance measures. Li and Liu [9] utilized a deep neural network to predict learner performance and reduce learner dropout using a cohort of 83,993 learners. They evaluated the performance using MAE and RMSE, resulting in values of 0.593 and 0.785, respectively. Kalaivani et al. [10] presented a predictive system to anticipate learner performance and enable timely interventions before potential failures in graduation. Logistic regression (LR), SVM, decision tree (DT), NB, k-nearest neighbors (KNN), and RF are evaluated to develop the prediction model. The NB classifier achieves remarkable precision, F1-score, and recall metrics of 0.93, 0.92, and 0.92, respectively. Nabil et al. [11] investigated deep learning methodologies to forecast the learner's academic performance and identify those at risk of failure. The proposed model achieved an accuracy of 89%, surpassing alternative models such as RF, DT, gradient boosting (GBoost), LR, and KNN. Saleem et al. [12] proposed an intelligent decision support system using ensemble ML to predict student progress. The suggested model improves prediction accuracy using ensemble approaches. The stacking model outperforms other ensemble methods. Hooda et al. [13] combined educational data mining and learning analytics. This study investigated the Open university learning analytics dataset (OULAD) and a fully connected network. This approach reaches an accuracy of 84%. Al-Azawei and Al-Masoudy [14] forecasted the academic achievement of 1938 students in OULAD by extracting demographic, behavioral, and engagement antecedents. This study achieves an accuracy of 88% with a prediction of one day before the final exam. Alshaikh and Hewahi [15] used three convolutional neural network (CNN) architectures to predict student academic success from two public datasets. Two feature selection approaches were tested: Principal component analysis (PCA) and DT. The experimental findings reached an accuracy of 94% on the first dataset and 84.83% on the second. Venkatachalam and Sivanraju [16] presented the student accomplishment prediction using the distinctive deep learning (SADDL) model for academic performance forecasting. The dataset includes 126 attributes related to demographics, academic performance, and physiological factors. The work employed long short-term memory (LSTM), deep CNN, and multilayer perceptron (MLP) and resulted in an accuracy of 91.71%. Wang et al. [17] introduced a convolutional residual recurrent neural network (CRRNN) to identify students at risk. The research utilized OULAD and achieved an accuracy of 82% over a 70-day prediction window. Gámez-Granados et al. [18] proposed an optimized ordinal classification algorithm (FlexNSLVOrd) to predict student performance. The paper used OULAD and applied various data mining methods. Adnan et al. [19] prevented student dropouts and enhanced academic achievement by devising a predictive model to identify at-risk students for early intervention in online courses, employing OULAD. They examined various ML methods where the RF performed well, achieving an accuracy of 92%. Hlioui et al. [20] offered a withdrawal prediction model for learners based on the OULAD. The study utilized five machine learning models for prediction, with RF having the greatest F-measure of 0.853. Al-Nawashi et al. [21] used a deep learning approach by presenting a new framework based on deep reinforcement learning (DRL) to improve cybersecurity and simulate harmful cyberattacks. The suggested approach outperformed findings from similar research with an accuracy of 98.82%, exploiting the CIC-IDS-2018 database. Bawaneh et al. [22] combines machine learning with the belief–desire–intention (BDI) model to tackle IoT security issues. The system demonstrated notable performance metrics, achieving 95% accuracy, an 87.4% F1 score, 90% precision, and 85% recall. These results underscore the system's viability as a robust solution for IoT cybersecurity.

This paper aims to use deep learning [6] to predict learner performance based on various tactics for selecting relevant features, reducing the computation rate, and avoiding overfitting. In summary, the study's main contributions are:

- Investigate the effectiveness of CNN [23] in predicting learners' performance.
- Use a dataset containing information about demographic, behavioral, and engagement antecedents.
- Utilize data preprocessing techniques to prepare data for convolutional neural network.
- Address the issue of class imbalance within the dataset.
- Apply automatic manners to search for the most hyperparameters; avoid doing too many tests.
- Extract the relevant features using three types of feature selection.

This structure of this paper is as follows: Section 2 proposes our methodology. Section 3 discusses the results. Section 4 summarizes the study's findings and identifies areas for future research.

2 MATERIALS AND METHODS

This study follows a structured sequence of steps, as delineated in Figure 1. Initially, a data preprocessing phase is executed. Following this, GridSearch Cross-Validation (GridSearchCV) is leveraged to find CNN's optimal hyperparameters for augmenting model efficacy. Next, three feature selection methodologies are implemented. The optimized hyperparameters ascertained in the preceding step are utilized to construct a series of CNN models. The training and testing sets are created through stratified cross-validation. Finally, both binary and multi-class classification tasks are conducted to evaluate the accuracy of each model.

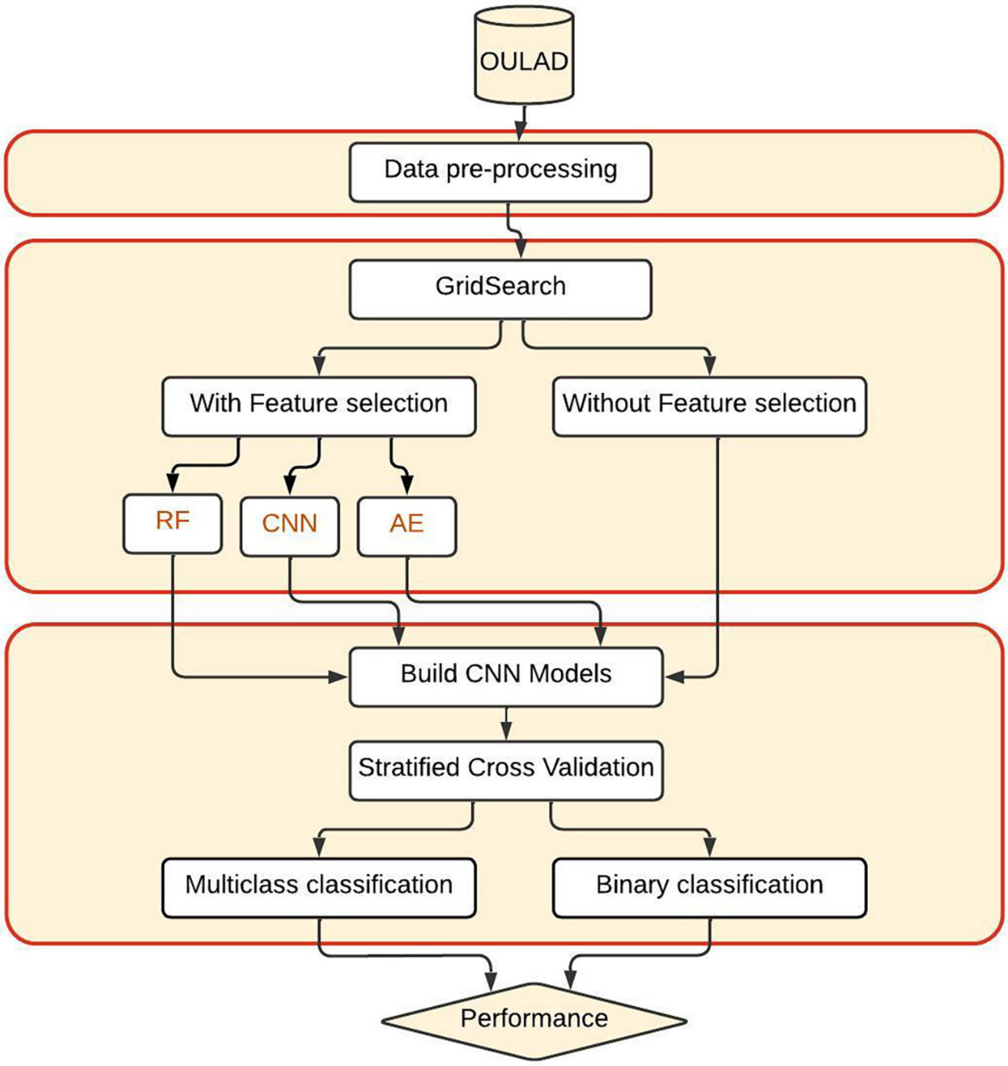

Fig. 1. Workflow of our proposed method

2.1 Data preprocessing

The OULAD [24] includes a comprehensive collection of information related to the learning process for 32,593 registered learners in 22 module presentations. OULAD is freely accessible and available as a set of CSV files. OULAD comprises detailed information on course registrations, learner demographics, VLE interactions, score assessments, and outcomes for each learner. The target variable consists of four categories labeled "PASS," "DISTINCTION," "FAIL," and "WITHDRAWN." Each category signifies a different level of academic achievement. The proposed data preprocessing strategy involves several steps described below:

a) **Data cleaning:** Data cleaning is the process of finding and correcting mistakes or discrepancies in every dataset before utilizing it to train machine learning models. A clean dataset produces more accurate forecasts and fewer mistakes.

The most typical steps taken in data cleaning are missing values [25], duplicate values [26], and outliers [27], which affect the performance of machine learning models. Therefore, a data cleaning step is mandatory to ensure optimal model performance.

b) Feature extraction: The OULAD contains seven files comprising detailed information about course registrations, learner demographics, VLE interactions, score assessments, and learner outcomes. The learner's assessments are found by merging *Assessments* and *StudentAssessment*. The learner's interaction with VLE is achieved by merging *StudentVLE* and *VLE*. The learner's information is obtained by elevating features from *StudentInfo*. The target variable for predictive models is the *Final_result*. This paper proposes the development of novel features called Wigeht_score and Pass_rate, presented as follows:

Weight_score: present the relationship between the assessment's weight and the score achieved by the learner in this assessment. Equation 1 expresses this relationship:

$$\text{Weight\_score} = \frac{\text{score} \times \text{weight}}{100} \tag{1}$$

Where Score is the learner score achieved in each assessment and Weight is the weight assigned to this assessment.

Pass_rate: This feature clarifies the criterion for assessing a learner's performance and indicates that a learner demonstrates mastery when he completes a considerable portion of the assessments and he achieves a score above 40, which represents a minimum passing threshold. Equation 2 presents the expression:

$$\text{Pass\_rate} = \frac{\text{nbOfSuccessfulAsse}}{\text{TotalNbOfAsses}} \times 100 \tag{2}$$

Where nbOfSuccessfulAsse is the number of assessments the student has successfully finished and TotalNbOfAsses is the number of assessments that the student takes.

c) Features scaling: In machine learning applications, the algorithms' performance frequently relies on numerical input attributes with similar scales, making feature scaling essential. The author in [28] emphasizes the significance of standardizing numerical characteristics within the range of 0 to 1. Equation 3 facilitated this process.

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3}$$

Where X_{max} and X_{min} represent the feature's maximum and minimum values, respectively, whereas X and X_{scaled} represent the value of the feature before and after feature scaling, respectively.

d) One-hot encoding: Machine learning algorithms work well when applied to datasets that contain numerical attributes. Datasets necessitate the imperative conversion of all text-based attributes into numerical representations. This work employed One-hot encoder [29] to transform each text attribute into a corresponding numerical format. This technique enhances the algorithm's ability to process and analyze the data effectively.

2.2 GridSearchCV

GridSearchCV [29] is a strategy that assists in thoroughly exploring crucial model hyperparameters, which optimize performance. It evaluates each combination, employing cross-validation to ensure the model generalizes well to unseen data. When the best hyperparameters are found, the model is retrained on the full dataset for optimal performance. The proposed GridSearchCV in this study is based on hyperparameters outlined in Table 1.

Table 1. The proposed GridsearchCV hyperparameters

Hyperparameters	Values	Signification
Conv_filters	[[32], [32, 64]]	The number of convolutional layers.
Dense_units	[[128], [128, 64]]	The number of dense layers
Epochs	[20, 50]	The different epochs for training
Batch_size	[32, 64]	The different batch sizes
Pool_size	[2, 3]	The different pool sizes
Kernel_size	[3, 5]	The different kernel sizes

2.3 Feature selection

Feature selection (FS) [30] is essential in machine learning to identify informative features for model development. The chosen features enhance learning performance. FS methods aim to isolate a relevant subset of features, optimizing learning efficiency and effectiveness. This work employed three feature selection methods CNN, RF, and autoencoder (AE). Each way is utilized in isolation to evaluate its influence on augmenting the classification precision. This isolation facilitates a comparative analysis of their efficacy in enhancing CNN model performance.

2.4 Building CNN models

The proposed CNN was formulated based on the findings obtained from GridSearchCV. Table 2 presents the CNN architecture for multi-class and binary classification. In binary classification, the Pass and Distinction classes were unified into a Pass class, whereas the Withdrawn and Fail classes were integrated into a Fail class.

Table 2. Proposed CNN structure for multi-class and binary classification

		Layer Type	Output Shape
Multi-class classification	CNN with AE FS	conv1d (Conv1D)	(None, 28, 32)
		max_pooling1d(MaxPooling1D)	(None, 14, 32)
		flatten (Flatten)	(None, 448)
		dense (Dense)	(None, 128)
		dense_1 (Dense)	(None, 64)
		dropout (Dropout)	(None, 64)
		dense_2 (Dense)	(None, 4)
	CNN with CNN FS	conv1d (Conv1D)	(None, 30, 32)
		max_pooling1d(MaxPooling1D)	(None, 15, 32)
		flatten (Flatten)	(None, 480)
		dense (Dense)	(None, 128)
		dropout (Dropout)	(None, 128)
		dense_1 (Dense)	(None, 4)
	CNN with RF FS	conv1d(Conv1D)	(None, 26, 32)
		max_pooling1d(MaxPooling1D)	(None, 13, 32)
		flatten (Flatten)	(None, 416)
		dense (Dense)	(None, 128)
		dense_1 (Dense)	(None, 64)
		dense_2 (Dense)	(None, 4)
Binary classification	CNN with AE FS	conv1d (Conv1D)	(None, 28, 32)
		max_pooling1d(MaxPooling1D)	(None, 14, 32)
		flatten (Flatten)	(None, 448)
		dense (Dense)	(None, 128)
		dropout (Dropout)	(None, 128)
		dense_1 (Dense)	(None, 1)
	CNN with CNN FS	conv1d (Conv1D)	(None, 30, 32)
		max_pooling1d(MaxPooling1D)	(None, 15, 32)
		flatten (Flatten)	(None, 480)
		dense (Dense)	(None, 128)
		dropout (Dropout)	(None, 128)
		dense_1 (Dense)	(None, 1)
	CNN with RF FS	conv1d (Conv1D)	(None, 18, 32)
		max_pooling1d(MaxPooling1D)	(None, 9, 32)
		flatten (Flatten)	(None, 288)
		dense (Dense)	(None, 128)
		dense_1 (Dense)	(None, 64)
		dense_2 (Dense)	(None, 1)

3 RESULTS AND DISCUSSION

This section summarizes the important findings from this work. It presents the evaluation result of the CNN model for predicting student performance. In the e-learning sector, learners who drop out before completing the course represent a minority. Figure 2 shows the distribution of our class percentages. These percentages confirm that our dataset is imbalanced, as the Withdrawn class accounts for only 1.07% of the entire dataset, while the Pass class accounts for 58.34%. The SMOTE gets a balanced dataset shown in Figure 3, where all classes are equally represented. Figure 4 presents that the CNN model's performance has increased by 8% in multi-class classification and 4% in binary classification after applying synthetic minority oversampling technique.

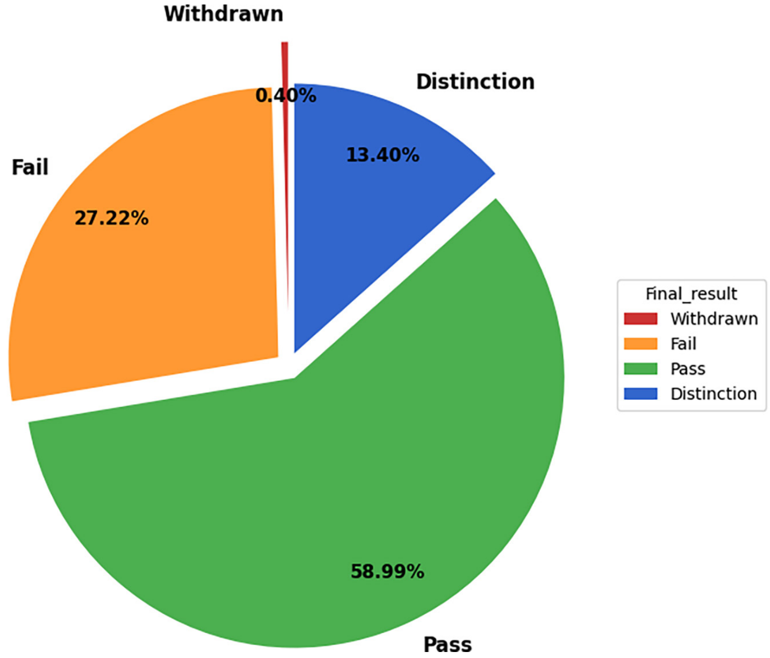

Fig. 2. The percentage-based distribution of classes before using SMOTE

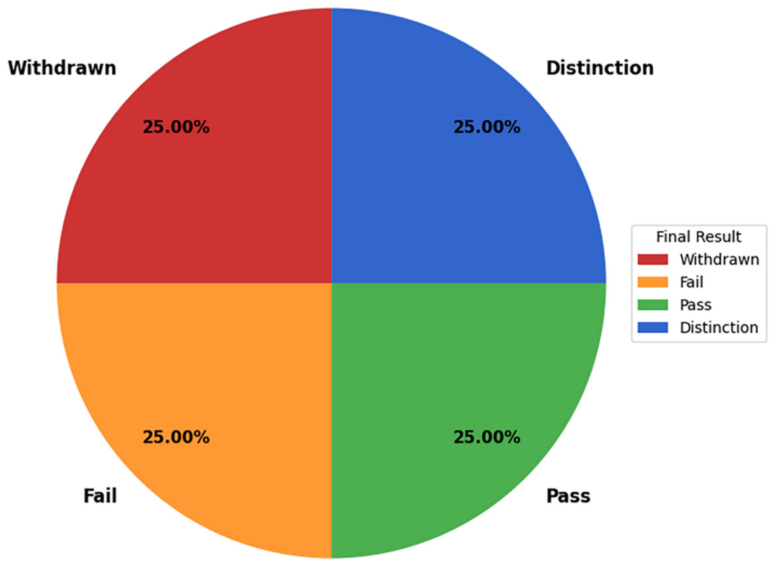

Fig. 3. The percentage-based distribution of classes after using SMOTE

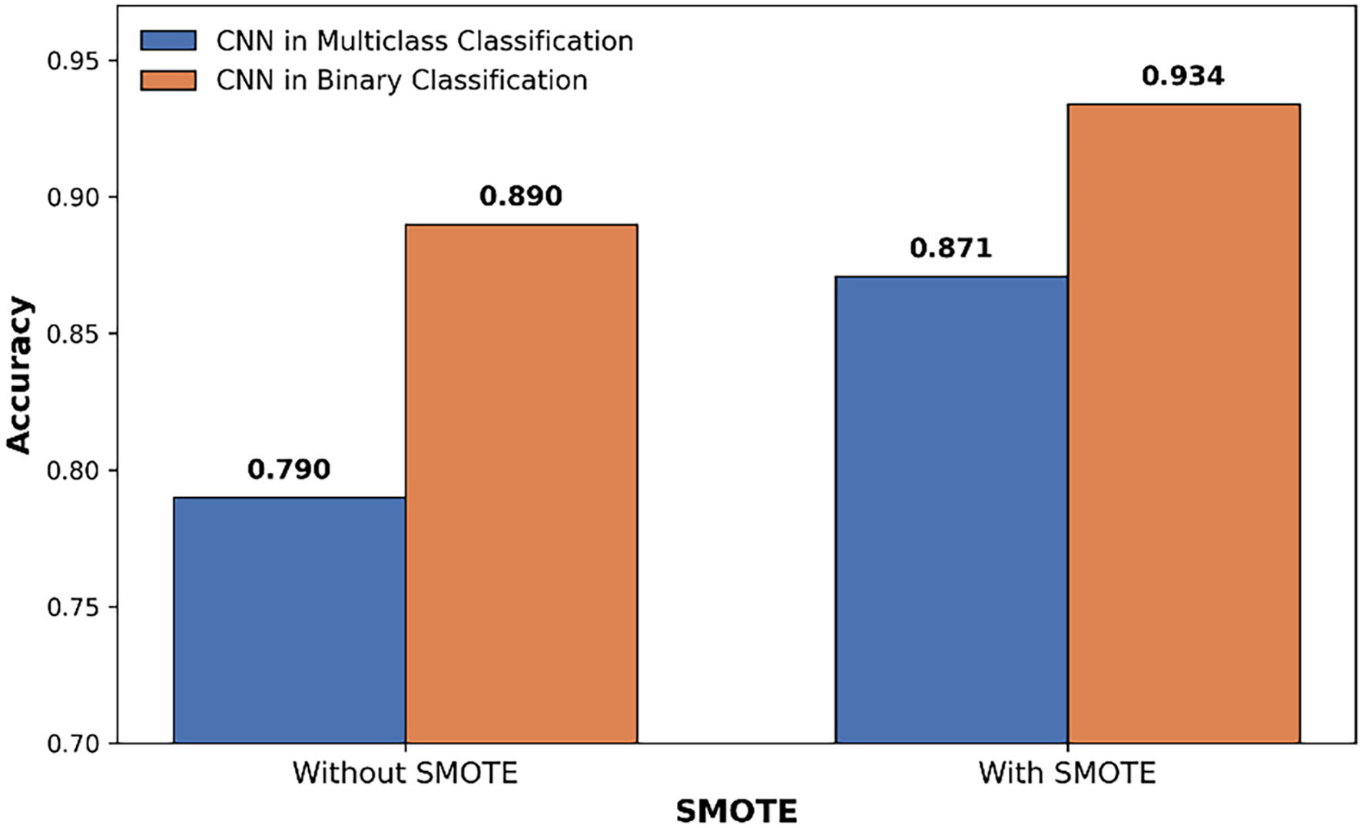

Fig. 4. Impact of SMOTE on CNN model performance

GridSearchCV finds the CNN model hyperparameters that offer efficient performance. Table 3 describes the results obtained. Employing this manner is a challenging stage in machine learning, since it requires significant computing resources and memory to explore many hyperparameter combinations.

Table 3. GridSearchCV result

		Batch Size	Conv Filters	Dense Units	Epochs	Kernel Size	Pool Size
Multi-class classification	With CNN FS	64	32	128	50	3	3
	With RF FS	32	32	128,64	50	5	2
	With AE FS	32	32	128,64	50	5	2
Binary classification	With CNN FS	32	32	128	20	3	2
	With RF FS	64	32	128,64	50	5	2
	With AE FS	64	32	128	50	5	2

Table 4 delineates a comparative examination of CNN architectures implemented on our dataset. The study shows that using CNN-based feature selection works better than the RF and AE methods, greatly enhancing the CNN model's performance. The confusion matrix and heatmaps for the CNN model with CNN-based feature selection (CNN with CNN FS) in both multi-class and binary classification are presented in Figures 5, 6, 7, and 8, respectively.

Table 4. Summary of proposed CNN result

		Class	Precision	Recall	F1-Score	Accuracy
Multi-class classification	With CNN FS	Withdrawn	0.89	0.89	0.89	**0.88**
		Fail	0.88	0.84	0.86	
		Pass	0.76	0.78	0.77	
		Distinction	0.99	1.00	1.00	
	With RF FS	With drawn	0.85	0.89	0.87	0.86
		Fail	0.90	0.79	0.84	
		Pass	0.71	0.76	0.74	
		Distinction	0.99	1.00	1.00	
	With AE FS	Withdrawn	0.82	0.92	0.86	0.85
		Fail	0.83	0.86	0.85	
		Pass	0.75	0.63	0.69	
		Distinction	0.99	0.99	0.99	
Binary classification	With CNN FS	Fail	0.94	0.93	0.94	**0.94**
		Pass	0.94	0.94	0.94	
	With RF FS	Fail	0.94	0.90	0.92	0.93
		Pass	0.91	0.95	0.93	
	With AE FS	Fail	0.93	0.92	0.92	0.93
		Pass	0.92	0.93	0.93	

	precision	recall	f1-score	support
Withdrawn	0.89	0.89	0.89	2176
Fail	0.88	0.84	0.86	2154
Pass	0.76	0.78	0.77	2099
Distinction	0.99	1.00	1.00	2135
accuracy			0.88	8564
macro avg	0.88	0.88	0.88	8564
weighted avg	0.88	0.88	0.88	8564

Fig. 5. Confusion matrix for CNN with CNN FS in multi-class classification

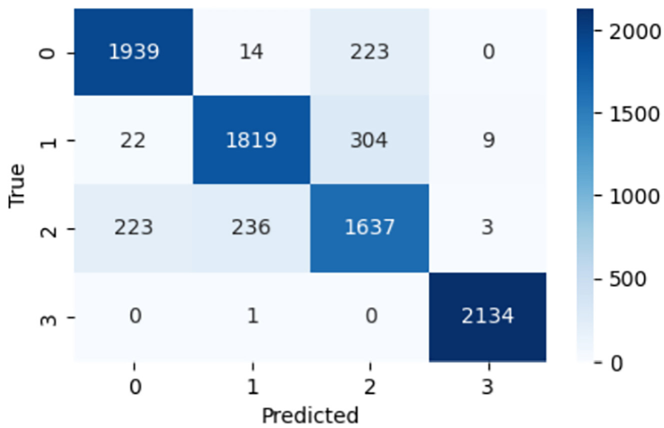

Fig. 6. Heatmap for CNN with CNN FS in multi-class classification

	precision	recall	f1-score	support
0	0.94	0.93	0.94	4289
1	0.94	0.94	0.94	4275
accuracy			0.94	8564
macro avg	0.94	0.94	0.94	8564
weighted avg	0.94	0.94	0.94	8564

Fig. 7. Confusion matrix for CNN with CNN FS in binary classification

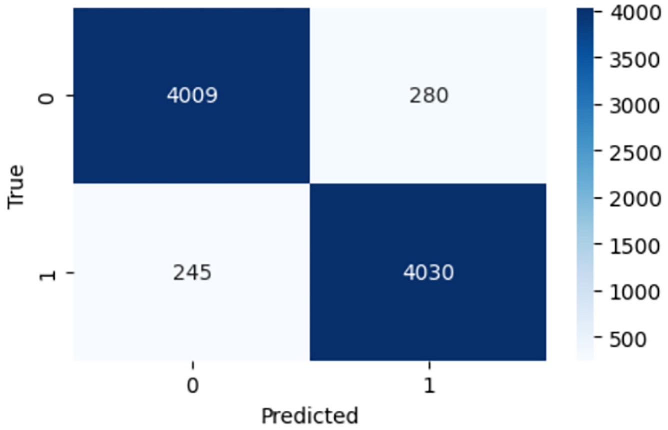

Fig. 8. Heatmap for CNN with CNN FS in binary classification

Compared to the antecedent, the proposed methodology surpassed previous works in the literature, which utilize the same dataset. Table 5 presents comprehensive findings. This research is among the limited studies that employ GridSearchCV and CNN. It's important to suggest solutions for failed learners. Those solutions enable rescuing them before it's too late.

Table 5. Accuracy comparison with previous works using the OULA dataset

Ref	Technique	Accuracy
[13]	FCN	84% in multi-class classification
[14]	M5P regression	88% in multi-class classification
[17]	CRRNN	82% in binary classification
[19]	RF	72% in multi-class classification and 92% in binary classification
[20]	RF	85% in binary classification
[18]	FlexNSLVOrd	85.5% in multi-class classification
Proposed CNN	CNN-CNN	88% in multi-class and 94% in binary classification

4 CONCLUSION

Predicting learner performance in e-learning before the final exam is essential for timely intervention and informed decision-making. Such intervention enhances learner performance and offers a customized educational experience for everyone.

This paper investigates the effectiveness of CNN in predicting learners' performance based on data extracted from the Open University Learning Analytics Dataset.

This work began by preparing the data for CNN using various data preprocessing approaches. The SMOTE resolved the problem of an imbalanced dataset and boosted the CNN model's performance by 8% in multi-class classification and 4% in binary classification. This study applied GridSearchCV to search for optimal hyperparameters, reducing the need for excessive testing and contributing to improved results. Most previous research ignored this approach of hyperparameter adjustment. The relevant features were extracted using three types of feature selection, which is crucial to enhance CNN performance. The findings indicated that the CNN-based feature selection approach surpasses both the RF and the AE. The proposed methodology yielded good results in terms of accuracy, achieving 88% in multi-class classification and 94% in binary classification, and outperforming earlier literature that used the same dataset.

The developed model will be incorporated into an e-learning web platform for empirical testing. This incorporation enables the assessment of efficacy and practical applicability. The future work aims to identify learner profiles to provide a personalized educational experience for everyone.

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