FCNN: The Hybrid Optimized Featured CNN Model for Academic Student Performance

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Abstract –

Analysing students' academic performance is a sub-set of EDM that deals with the extensive data collection from an ES (education system). It aims to extract data from this information meaningfully to enable the ES. Student performance is a vital factor in calculating teaching quality in colleges. The main issue of calculating if a student will fail/pass at a specific academic discipline based on a student's grades established through the semester is complex and extremely based on several situations like; course, examinations, semester, and instructions. The research article has implemented a novel classification algorithm FCNN (Featured convolutional neural network), to calculate academic student performance. The evaluation of the FCNN and S PRAR methods, which are between, were calculated and compared to indicate the student performance. The database measured the different instances and attributes, taking "The University of Jordan, Amman." The outcome defines that the research method attained a classification accuracy of 0.95 per cent. Lastly, this analysis describes a contribution to the early-stage classification of students at high-risk of failure and DL (deep learning) techniques.

Keywords *-EDM (educational data mining), DM (data mining), S PRAR classifier, FCNN classification method, DL (deep learning).*

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1.Introduction

EDM (educational data mining) is a developing field of research, i.e., being utilized to search for educational information for different academic determinations[1]. The primary use of EDM is to analyze students' academic performance[2]. DM (data mining), the interpretation and analysis of student academic performance are observed as reliable analysis, calculation, and classification tools [3].

In the present era of the knowledge economy, the students are the main element of the socio-economic development of any city or country, so keeping their performance on the track is necessary.

DM algorithms are functional to analyze hidden knowledge and designs, which assist academicians and administrators in decision-making regarding the delivery of guidelines. DM algorithms have applications in various fields such as health, marketing, banking, retail business, bio-informatics, etc., to improve effectiveness[4] and productivity.

Education plays a significant role in the growth of any nation-state. The education in PAKISTAN has enhanced in the previous few years. The student academic performance of high-school scholars is a severe concern for teachers, the education department, the government, and parents. Students' presentation at the secondary level is highly influenced by their schooling, social, family background, etc.

EDM is used to examine a crucial task; analyzing student performance. The study predicts the value of an unverified variable that explains the student's result (pass/fail), GRADE, MARKS, etc. Classifying scholars' success, attributes, and failures are the main fields in this analysis's related works. Each investor who relates to this area wants an EWS (early warning system) to classify education in the early-phase. An EWS optimized the learning costs and space and time complexity. One of the most prevalent challenges in enhancing educational processes' quality is improving student performance. Tutors may update their training methodology to achieve the

necessity of degrade performance students and offer added regulations to worthy students [5,7]. The classification outcomes could help students understand how good or bad they would achieve in a course and may take phases.

The literature review analyzed the different rule mining methods, such as; S PRAR [19] and RAR[6] rule mining, to classify academic student performance. It considers only three databases to highlight that the S PRAR model is reliable for the method issue.

The main contributions of this proposed analysis toward educational data mining are: (i) To review the recent academic performance prediction model and state the clear problem definition of the same. (ii) To incorporate the optimization-assisted deep learning concept to enrich the models' performance on accurate prediction. (iii) To propose new hybrid optimization with BFO and ALO algorithm for parametric fine-tuning of deep learning; this ensures a better convergence rate than the conventional models. (iv) To Train the optimized deep learning with the CNN model with positive and negative instances that evaluate the Rule mining approach. And (v) To calculate the presentation of the research model over other state-of-the-art models concerning different performance metrics, precision, and recall of prediction.

To study data using the classification method using the FCNN algorithm, well-defined classification methods like S PRAR is being utilized for prediction determinations. The quality of a classification method is calculated by its capability to explore the undefined designs precisely. The proposed work aims to construct the FCNN algorithm that categorizes academic student presentations as pass or fail.

The rest of the research article is managed as trails: Sect. 2 defines the prior work that mentioned the machine and deep learning academic performance analysis. Sect 3 represents the existing findings of previous research analysis. Sect 4 describes the research methodology, and the section is related to data gathering, preprocessing, feature extraction, selection, and classification. Sections 5 and 6 illustrate the experiment result in analysis, and the conclusion and further work of this proposed analysis have been described.

2.RelatedWork

They outline various current machine and deep learning research analyses for assessing academic students' performance in EDM (educational data mining). Silva, J., et., (2021) [8] proposed an artificial intelligence model for predicting academic performance. The neural network was used for the analysis of the performance of students. A backward propagating approach was used to develop a multilayer perceptron neural network to classify the chance to dominate the competition. The classification performance rates were very high, with an average of 74.98 per cent, including all programs, demonstrating the determinants' usefulness in forecasting educational attainment. Surenthiran et al. (2021) [9] designed a forecasting model and proposed a computational intelligence approach.

Participants were grouped using a DL-based technique known as a BDNN (deep belief neural network) with atomic searching improvement optimization—a cognition convergence method with several spiralled restricted Boltzmann models powers. The presented model was built using an open learning collection at first. It was pre-processed during the first stage, and in the second stage, it was categorized. DBNN made modifying the learning rate variables hard in the second stage. The primary level of education was automatically estimated via the ASO optimizer. Evaluation metrics were evaluated by measuring the suggested research, and the results were higher than previous techniques. The conceptual model improves to a degree of accuracy of 90 per cent and a lower false-positive value of less than 20 per cent. Hussain, et al. (2021) [10] analyzed that deep learning was gaining popularity in various fields, particularly computer vision applications with a massive volume of data. The authors used a deep CNN to create a predictive framework for analyzing learners' educational success. The authors mainly used evolutionary computation and regression analysis to perform the classification of the collection. Overfitting was a problem that must be addressed for algorithms with fewer samples. As a result, the specifications could be tweaked to ensure quality and safety. Only with the parameter of k = 3 does the learning algorithm record a relative standard performance of 1.61 MAE and a loss of 4.7. On the other hand, the coefficient of determination provides a loss of 6.7 and an MAE scoring of 1.97.

The deep network outperformed the multiple LR. Huang et al. (2021) [11] research looks into the possibility of using Artificial Intelligence to establish the degree of probability for forecasting academic achievement. The authors presented 2 different methods for predicting student achievement: loaded SVM and ANN training. To achieve a coarse-grained classification algorithm, a component-loaded SVM was used, in which the effect of individual variation on the result was determined utilizing attribute selection proportions (pass (P1) or fail (P0)). ANN training was then used to enable fine-grained, multiple-class learning of the P1 and P0 categories, with descriptive rating scales ranging from D to A+. The investigations and accompanying elimination analysis that used student statistics across two Portuguese elementary levels had shown that this hybrid approach was efficient. Tsiakmaki et al. (2021) [12] designed a student performance analysis based on ML. The proposed system was based on active learning. The fuzzy system was used to enhance the results of the student performance prediction. Effective learning improves the cost and time of labeling operation by using a minimum collection of labeled data, including a huge number of separate information, most efficiently. Bujang et al. (2021) [13] thoroughly examined machine learning strategies for predicting ultimate academic achievement during the first coursework while boosting prediction accuracy. Throughout the study, synchronous generators would be emphasized. Initially, the authors used a sample of 1282 actual learners' course grades to estimate the validity of 6 well-known neural network models: K-Nearest Neighbor, Decision Tree, LR, NB, RF, and SVM. Secondly, the authors presented a classification method. The framework was based upon the synthetic minority oversampling method, including two selections of feature strategies to minimize overfitting and erroneous outcomes generated by unbalanced multi-classification. The findings indicate that integrating the conceptual model using random forest leads to a significant enhancement, with the maximum 99.5 percent F-measure. Bhutto et al. (2020) [14] offered a method for estimating learners' academic achievement which employs autonomous computational methods such as LR and SVM. The outcomes of several trials implementing multiple techniques were examined, and it was discovered that the sequential minimal optimization technique exceeds regression analysis in terms of effectiveness. And also, the information gained from the study could assist institutions in predicting learners' future behaviour and evaluating the achievement as acceptable or unfavourable. The goal was to forecast potential student outcomes and provide enough effective techniques for identifying the most significant elements to concentrate on, such as instructor achievement and educational incentives, to reduce the learner attrition rate. Liu et al. (2020) [15] proposed that combining student performance and activity variables was critical for improving proper channels; each variable had a varied effect on student achievement. As a result, the research provides a unique method for predicting academic achievement that incorporates all these students' performance and exercising variables, the learning algorithm, and the learning mapping approach. The authors used deep learning for a dynamic collected classification model to be more precise. Furthermore, a fusing awareness approach that relies on a multilayer perceptron structure was applied for classification and prediction. Additional testing on such a dataset demonstrates the method's efficacy and applicability. The proposed approach had a 98 percent accuracy rate, higher than prior techniques. Song. et al. (2020) [16] proposed a structure that predicts educational achievement dependent on successive involvement. Activation detection, as well as sequence prediction were the two primary categories. The interaction detector used the benefits of a deep convolution system to find learners' involvement tendencies as they go about their regular tasks. The consecutive predictors predict the connection between involvement subspaces and sociodemographic variables using the extended short attention span framework. The findings show that the algorithm performs them in the interaction detection method compared to various diverse, comprehensive neural network models. Jain et al. (2019) [17] analyzed the effectiveness of several supervised learning models on an academic database to predict academic achievement was examined in the research. Although there was a significant amount of literature on the classification and prediction, the various issues related to an earlier study in the following ways: rather than using a classification algorithm of the pass or fail,

the authors employed a multiclass classification during which learners were categorized into 3 groups: bad, medium, as well as outstanding performers. The authors constructed a more appropriate prediction with 95 percent precision and less computational efficiency using pre-processing steps, extraction of features, and returning parameter sets, which several researchers did not concentrate on; the authors examined the association among particular features using a similarity. The authors had to use data transformation, extraction of parts, and higher accuracy of optimization techniques to build a classification model, which was not concentrated among many researchers defined in table 1.

Table 1. Several existing methods of academic performance prediction

Author's Name	Techniques	Issues/research gaps	Parameters	Further improvement
Chango et al., (2021) [7]	Data diffusion-based approach	Need to extract semantic level features	Acc AUC	A hybrid technique with optimization will be implemented in the future.
Surenthiranet al.,(2021) [9]	DBNN with ASO (Atom search optimization)	Limited dataset High computational time	Acc Error rate	The optimization method will be improved for effective outcomes.
Hussain et al., (2021) [10]	DL-based regression analysis methodology	Un-clear network duration	Acc	Massive data will be collected for the trained model.
Huang et al., (2021) [11]	ANN and SVM algorithm	Problems are data argumentation	Acc Pre Rec	Multi-class classification model will be applied
Tsiakmaki et al., (2021) [12]	Fuzzy-based system	Reduced outcomes of feature-extraction	Acc	The soft computing method will be implemented for future improvement.
Bujang, et al., (2021) [13]	ML-based numerous class prediction	minimum Acc	F-measure	Overfitting problems will be solved.
Bhutto et al., (2020) [14]	Supervised learning-based process	The necessity to remove hidden information	F1-score Pre Rec Acc	crossbreed features will be released for effective outcomes.
Liu et al., (2020) [15]	Fusion attention-based DL model	Reduced outcomes of feature-extraction	Acc AUC RMSE MAE	NN method will be improved for more effective outcomes.
Song. et al., (2020) [16]	SEPM	minimum accuracy	MSE F1 score Rec Acc	More demographic attributes will be fetched for more precise results.
Jain et al., (2019) [17]	Gradient-based extreme boosting model	They essential to utilize behavioural metrics	Pre Acc Rec Execution time F-measure	The optimization method will be proposed for further development

Table 2 describes various research performances attained in educational DM literature for classifying or predicting the evaluation of students.

Table 2. Previous results on the student's performance classification or prediction

Author Name	Model	Parameters	Values
Wilson Chango et al. [7]	Jrip	Acc	80.7
		Auc	0.84
	Nnge	Acc	82.4
		Auc	0.91
	RT	Acc	75.4
		Auc	0.83
Hussain et al. [10]	LR	MAE Score	1.97
		Loss	6.7
		R^2	0.89
Huang et al. [11]	IGR-FWSVM+ANN	RMSE	0.57
		MAPE	0.26
Gabrela et al. [19]	SPRAR	Pre	0.93
		Sen	0.91
		F-score	0.92
		NPV	0.59
		Spec	0.67
		Auc	0.79

Abbreviations: ANN (artificial neural network), SVM (support vector machine), LR (logistic regression), Pre (precision), Sen (sensitivity), Acc (accuracy), MSE (mean square error), MAE (mean absolute error), Auc (area under of curve), DT (decision tree), EDM (educational data mining), DM (data mining), CNN (convolutional neural network), DBNN (deep brief neural network), ML (machine learning), DL (deep learning). S PRAR (students' performance prediction using relational association rules), RAR (relational association rule), SEPM (Sequential engagement-based academic performance model).

3. Problem Formulation

In higher education institutions, academic achievement is essential. A remarkable record of educational attainment has become one of the prerequisites for a high-quality institution. The increasing volume of data formed in VL (virtual learning) atmospheres shows the potential to learn statistics and problems relating to compatibility, privacy, pedagogy, and institutional examples. As an outcome, novel methods and technology platforms are mandatory to evaluate indicators and deliver personalized programs and support to users such as; learners, academic staff, and guardians. Cognitive and administrative paradigms must also be implemented by taking insights and viewpoints of the customized frameworks and designing to help effective learning. Also, the availability of data from numerous sources shows several concerns such as; confidentiality association, scalability, confidentiality, and institutional business associations.

Predictive analysis is commonly used in EDM methods to evaluate academic achievement. Numerous operations are employed to develop predictive analysis, including regression, categorization, and segmentation. Categorization is the most common task for estimating academic achievement [8]. Under the categorization task, numerous techniques (RF, DT, SVM) have been used to evaluate academic achievement. The existing methods of educated performance prediction are suffered from various challenges [18], such as;

- Classification issues
- Inaccurate prediction
- Data argumentation issues
- Overfitting issues
- SPRAR classifier does not apply to regression problems. Currently, the SPARP classifier only manages binary relations among the feature vectors.

4.Existing Techniques

This section has described the existing classification methods like; S PRAR and Rule Mining.

4.1. Classification Model Using S PRAR

In the classification phase, when a novel [19] query instance *s* has to be categorized, they calculate the probabilities p+(s) and p-(s) that the query instance goes to the positive and negative groups, resp. The intuition behind significant possibilities was that the connection of model s to a specific group c is very probable to inclined by the assurances of the principles from RARc that are identified in the instance s, but also by the directions from RAR-c that are not specified in the instance s. By –c they represented a class that conflicted with c. Preliminary from this intuition pc (s) will calculate not only how 'close' the instance s is the group c, but also how 'far' it is from the opposite class –c.

4.2 ARM (Association Rule Mining)

It is a significant DM functionalities and methods that investigators have analyzed. Extracting ARs (association rules)[20] is the primary concept of DM. DM for ARs in the dataset of sale transactions among items is a significant area of the proposed database. The main advantages of these principles are classifying undefined relationships and generating outcomes that can achieve the basis for decision-making and classification. The detection of ARs is separated into two steps: categorizing the frequent itemsets and creating ARs.

5. Proposed Work

This section discusses the proposed methodology description and flowchart. Figure 1 represents the proposed design, which deals with data mining and deep learning. This research method uses the new hybridization of the optimization and DL (deep understanding) method to classify academic performance prediction. Pre-processing, feature extraction, new hybrid feature extraction, classification. Generally, it will contain academic records with various steps. Most researchers can collect the database from online sites. After the collection phase, it will upload the input data and verify the probability of the database when the database will search. Before classifying the academic records, the following steps are developed for databases. The pre-processing data phase takes place, which will manage the description in the matrix and is processed for practical calculations. The academic records will be processed for feature extraction using PCA. It will reduce the dimensional of the process record matrices. After the feature extraction process, the new hybrid optimization with BFO and ALO algorithm will be developed. It will extract reliable instances from the academic records. The training procedure will complete by an optimized FCNN deep learning algorithm. Once the feature extraction and selection process are complete, the network learns the design and creates an optimized DL model. This optimized DL model will implement to predict the academic records and evaluate the performance metrics such as precision, recall, etc. The proposed algorithm steps are defined in Table 3. These proposed performance metrics will compare with the existing models.

The proposed architecture will define several phases like collecting academic records.

Table 3. FCNN Proposed Classification Algorithm

Pseudo Code: FCNN algorithm
Input: Academic Student Performance
Output: classify the student performance Initialization Upload the database ($data_b$) in the string and numeric format **Pre-processing Phase:** Data cleaning $C_l = data_b$ **Feature Extraction Phase:** D = C_l; [r,c]=size(D); Calculate mean and transpose data. D1 = mean(Data')'; Da = D-repmat(D1,1,c); co_var = D*D'; co_var(isnan*co_var)=1; [V,E] =eig(co_var); E1 = diag (E); [r1,c1] =size(-E); E1 = E(c1); V1 = V(:,c1);

a=0;

for i=1:size(E,1)

if (E1(i)>0)

a=a+1;

end if

end for

v =V(:,1,a);

Da (isnan(Da)) = 1;

Feature_data = v'*Da;

Feature Selection and Classification Phase:

Initial metrics :FFn, Search_sp, num_of_ants, ant_lion locations, max no. of. Iterations X.

Output:

Create the FFn, rand_pop, ant loc, antlion, loc, elimination-dispersal loop

Evaluate the FFn

S1 = 0;

While (S1<=S)

For each ant_loc do

Select an ant_lion using TS (tournament selection)

Glide the ants towards the ant_lion and update it.

Create rand_walk and normalize it

Revise the ant loc

Create a random vector and do a warning procedure

Calculate chemotaxi

Sort the metrics and re-produce the loop

Search current_BS (best-solution)

End for

Evaluate the fitness of all ants.

If BS is optimized then stop

Else go to step 3.

End while

Return BS. // Selected feature sets.

Input (28*28*1)

Conv_1 (5*5) kernel valid padding

Max-pooling (2*2)

Conv_2 (5*5) kernel valid padding

Max_pool (5*5)

Fully-connected NN (ReLu activation)

Fully-connected NN

Output : Classify the student performance

Evaluate the performance metrics: precision, recall, etc.

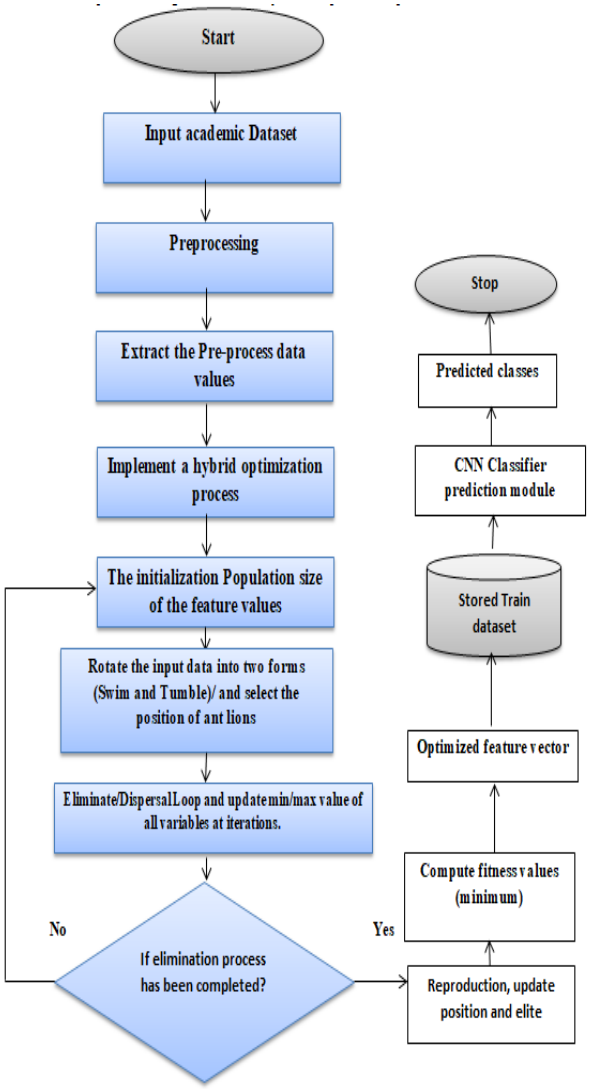

Figure 1. Flowchart with FCNN algorithm

6. Results and Discussion

This section defines the simulation outcomes attained by calculating the performance of the FCNN classifier and discusses the results and comparative analysis to related work.

6.1. Dataset Analysis

This section discussed the proposed work

dataset. Generally, this educational database is composed of LMS (learning management system)[21], known as kalboard 360. The database comprises four hundred eighty student-records and sixteen features. The feature sets are detected or classified into three main types such as;

- Demographic feature sets like nationality and gender.
- Academic background feature sets like an educational stage, grade-level, and section.
- Behavioural feature sets like raised hand-on class, OR (opening resource), answer analysis by parents, and school satisfaction.

The database is gathered through 2 academic semesters: 245 students' lists are composed during the 1st semester, and 235 student records are composed during the 2nd semester.

The database is shown in table 4 and comprises the school attendance feature. The students are detected into two types based on their ABSENCE days: 191 students exceed 7 ABSENCE days and 289 ABSENCE days under 7.

Table 4. Description : Dataset[21]

Gender	**NationalITy**	**StageID**	**Semester**	**Relation**	**Announcements View**	**Discussion**	**Parent Answering Survey**	**Parentschool Satisfaction**	**Class**
M	KW	lowerlevel	F	Father	2	20	Yes	Good	M
M	KW	lowerlevel	F	Father	3	25	Yes	Good	M
M	KW	lowerlevel	F	Father	0	30	No	Bad	L
M	KW	lowerlevel	F	Father	5	35	No	Bad	L
M	KW	lowerlevel	F	Father	12	50	No	Bad	M
F	KW	lowerlevel	F	Father	13	70	Yes	Bad	M
M	KW	MiddleSchool	F	Father	0	17	No	Bad	L
M	KW	MiddleSchool	F	Father	15	22	Yes	Good	M
F	KW	MiddleSchool	F	Father	16	50	Yes	Good	M

6.2. Evaluation Parameters

For calculating the proposed system performance of the FCNN algorithm on the testing database, the proposed matrix for two possible groups, such as pass/fail, will be calculated on a test set, like the pass group is the positive and the fail group is negative. The matric comprises the following values such as; T_p (true positive), F_p (false_positive), T_n (true_negative), and F_n (false_negative) values.

The proposed work has used the performance metrics such as; precision (positive-class), recall (sensitivity), etc. These procedures range from (0,1), and maximum principles define better classifiers.

- *Precision (positive-class):* It is the proportion of the accurately predicted cases to the total no. of mispredicted and accurately predicted cases.

$$Pre = \frac{t\_p}{t\_p+f\_p} Pre = \frac{t\_p}{t\_p+f\_p}$$ .... *(i)*

- *Recall (sensitivity):* It is the proportion of the accurately predicted cases to the total no. of unpredicted and accurately predicted circumstances.

$$rec = \frac{t\_p}{t_p+f\_n} rec = \frac{t\_p}{t_p+f\_n}$$ .... *(ii)*

6.3. Results and Discussion

MATLAB simulation tool was utilized to calculate the research classification algorithm and to make

comparisons. Various simulations were shown successively in this analysis to predict academic performance analyses. The comparison was made complete several S PRAR and FCNN algorithms.

Moreover, comparative analysis has been achieved to determine performance enhancements in various algorithms. The simulation analysis predicted the FCNN algorithm in classifying student educational performance at the different levels.

The DL (deep learning) classifiers comprising S PRAR and FCNN algorithms were applied after the data pre-processing step. The calculation outcomes defined that between different classification algorithms, FCNN outperformed the other methods, attaining maximum precision and recall, as illustrated in figure 2. The figure has defined two phases: (i) The bar chart represents the method's performance in terms of precision and recall. (ii) It represents the performance of methods in table 5 form through similar calculations.

Table 5. Proposed Parameters: FCNNalgorithm

Algorithms	Precision	Recall
FCNN	0.95	0.93
S PRAR [19]	0.93	0.91

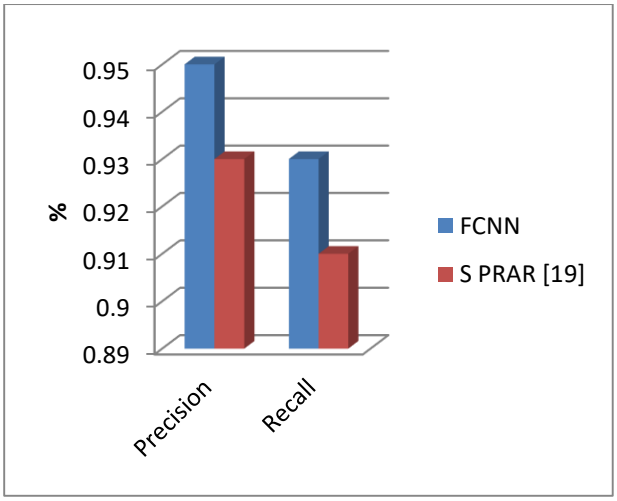

Figure 2. Experimental Results

Figure 2 defines the precision and recall for the FCNN and S PRAR algorithm on the considered EDM (educational data mining) dataset. Table 4 and figure 2 considered, for an academic dataset, a precision value of 0.95 and recall value of 0.93 as compared with the existing S PRAR algorithm. The research work has studied the simulation outcomes from table 5 and the comparative analysis with proposed and existing algorithms. The research FCNNalgorithm has achieved the maximum precision and recall rate, and the number of students' calculations during the semester must be increased.

7. Conclusion and Future Work

This article overviewed a new classification (FCNN) algorithm based on CNN (convolution neural network) for detecting the accomplishment of an academic course depending on the students' grades established through the academic semester. Simulation analysis on academic student performance analysis database collected from *"The University of Jordan, Amman."* has defined a better performance of the FCNN algorithm. The attained simulation analysis emphasized that the proposed classifier is improved than or similar to the rule mining model already developed in the educational data mining survey for student performance.

The main benefit of the FCNN algorithm overviewed in this article is its simplification, as it is not particular to the academic performance analysis task. FCNN is a classification approach that may be developed to classification issues in which a set of feature sets illustrates the instances from the training database. Any category of feature sets may be utilized in the research method and numeric or labelled between the feature sets. FCNN may be adapted to overfitting issues other than the student performance task.

The proposed method's further improvement will be analysed on a vast database with more attributes. It will be carried out to extend the simulation calculation of FCNN in the other analysis.

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