Prediction of Children's Learning Effectiveness Using Fine-Tuned Seagull-Optimized Weighted K-Nearest Neighbour (FSOA-KNN)

Shuai Xin, Yaqi Guo*, Nannan Ju
Departmentof Teacher Education, Weifang Engineering Vocational College, Qingzhou, Shandong, 262500, China
Corresponding author e-mail: anna111211@sina.com

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To predict children's learning effectiveness using data mining (DM) technology, addressing the challenge of unemployment among medium- and relatively low-risk learners. With the rapid expansion of academic institutions, the need for accurate prediction models becomes critical. A novel fine-tuned Seagull-Optimized Weighted K-Nearest Neighbor (FSOA-KNN) strategy was proposed to improve the prediction of learning outcomes. The research involved 300 students, and their features were collected and analyzed to assess learning effectiveness. Data preprocessing included min-max normalization to scale features within a defined range, ensuring consistency and reducing bias. Experimental results showed that the FSOA-KNN model achieved an precision of 96.5%, accuracy of 98.7%, F-measure of 95.5%, and recall of 96%. These results demonstrate the model's effectiveness in forecasting children's learning efficiency and identifying students who require additional guidance or counseling. Additionally, the model's performance was compared with traditional KNN and other optimization methods, demonstrating its superior prediction accuracy.

Povzetek: Predstavljena je nova hibridna metoda FSOA-KNN, ki združuje uteženo KNN in optimizacijo po vzorcu morskih galebov za napovedovanje učne uspešnosti otrok na podlagi večdimenzijskih podatkov.

1 Introduction

Education is one of the most important accomplishments and prerequisites for a person to have access to the truth, progress, personal recognition, and accurate knowledge. It is considered one of the cornerstones of human existence [1]. A student goes through multiple phases of education: primary, secondary, and higher education. After completing these stages, students may enroll in colleges, universities, or other educational institutions.

Education teaches individuals to think, distinguish between good and bad, and make judgments. It aids in knowledge and information acquisition and helps individuals successfully integrate into society, where people become prosperous.

Monitoring teaching and learning activities in an educational setting continuously is necessary to give students a high-quality education [2]. Because of the abundance of data in educational databases, this is typically challenging nevertheless, big data and ML, two recent technological advances; provide solutions for all of these issues. Big data refers to a collection of approaches and strategies that demand novel combinations to extract significant hidden values on a huge scale from a variety of intricate datasets. While the technology can identify pattern in analysis of data to uncover information that has been buried and facilitate decision-making, it is also incredibly useful.

Decision-making processes use more data since different information technologies are developing so quickly [3]. The difficulties in storing, handling, and evaluating the data grew along with the volume and complexity of the data that was gathered. An exponential rise in demand led to the development of data warehouses and new data management systems that surpassed the capabilities of basic relational database systems. A new term for the field of data analysis is data mining. To put it simply, the tedious, repeated process of finding new patterns in large-scale data sources is known as data mining. Associations, trends, linkages, and natural groupings, to improve evidence-based decision-making.

A plethora of knowledge is now easily accessible due to internet technology. Technology has applied in variety of way in the aforementioned situations to increase learning [4]. The world's current focus is on utilizing data mining techniques to better understand learning trends and the effects of alterations in learning environments and methods. Decision makers can use this knowledge to improve the quality of education, as there are large databases at their disposal and the fields of EDM and LA are fast developing.

Data mining can be applied to extract interesting and pertinent information from data. It encompasses various activities, including clustering, classification and prediction, and association rule mining. Predictions may have biases since the provided data may not be typical of all children. Models that predict might not adapt well to various populations, for instance, if the dataset mostly includes children from particular geographic or demographic origins.

The primary goal is to improve children's learning efficacy by implementing a fine-tuned seagull-optimized weighted k-nearest neighbor (FSOA-KNN) approach.

The remaining research falls under the following categories: Section 2deliberates related works. Methodology in Section 3. In section 4, the results of our methods will be assessed. Section 5 contained the conclusion.

2 Related work

The pursued monitoring students' academic progress, identified the danger, and solved a categorized problem (successful or unsuccessful) examined [5]. Using SPSS Modeler 18, the experiment employed classification models derived from supervised learning methods. The highest specificity value was attained by the C&RT model, which performed the best.

The Orange software was used for DM procedure and it used DT rule has identify the traits of student performing at moderate, high, and low levels has investigated [6]. It found that the most important predictor was the students' prior academic performance, along with a few demographic and psychological characteristics.

The methodology labeled student history data was utilized to train the regression model and decision tree classifier after Preprocessing had been done on the acquired data to enhance its quality has proposed [7]. The outcomes obtained demonstrated the value and efficacy of ML technologies in predicting student achievement.

Five ML techniques were used in [8] such as SVM, DT, NB, KNN, and the Federated Learning model. Research presented there showed how students made optimal use of learning data from several institutions while safeguarding data privacy, which promoted ML and EDM for the estimation of academic achievement.

The ML model's performance and compared the use of several data mining algorithms has evaluated [9]. The DM approach to performance analysis verified the effectiveness and correctness of the learning model, producing accurate and genuine forecasts.

The impact of EDM and LA on adaptive learning has investigated [10]. The empirical data supports the main goal of the possible integration of LA/EDM into common strategic scheduling for education.

The FA-BiGRU-consideration prototype produced the best prediction forecast and performed comparably in variant method analysis when related to individual models like the Back Propagation Neural Network, RF, Linear Regression (LR), GRUand ablation tests [11]. It means that a great deal of potential to change the traditional education sector, guarantee the country's talent pool continues to grow, and offer data references for bettering educational activities.

The past performance in similar courses to predict a student's success in a given course [12]. Massive data sets can be mined for hidden patterns using a range of data mining techniques. The experiment instructed that student data provide pertinent information and therefore comprise among others, SVM, ID3, C&RT, and Random Forest.

To determine which instructional strategies have improved student performance, investigated [13] examined the association between various factors, such as gender, parents' qualifications, exam preparation, and students' exam results. The results show that student's chances of passing exams were significantly impacted by their participation in test preparation courses.

The NB a probabilistic classifier using Bayes' theorem, assuming feature independence, effective for predicting categorical learning outcomes. ID3 a decision tree algorithm selecting attributes with maximum information gain to predict learning effectiveness based on student features. SVM a supervised algorithm separating data with a hyper plane to classify children's learning effectiveness with high-dimensional feature handling. k-NN a non-parametric method classifying learning effectiveness by comparing nearest feature similarities based on majority voting in k neighbors has examined [14]. Table 1 shows the comparative of applied technologies.

Table 1: Comparative of applied technologies

Reference	Applied technology	Discovering	Benefits	Limitation
Tosun et al. [5]	SPSS Modeler 18, C&RT	Academic progress tracking was identified and resolved, with the best specificity using the C&RT approach.	Efficient for supervised learning, particular outcomes	Requires knowledge of SPSS Modeler; may not translate to other software
Roslan et al. [6]	Orange software, DT	Traits of low, moderate, and high student performance were identified.	Results that are comprehensible and highlight key indicators	Restricted to decision tree functionality and struggle to manage intricate interactions
Yousafzai et al. [7]	Regression model, Decision Tree classifier	predicted academic success using historical data	Effectively uses past data and enhances the quality of the data	The accuracy of preprocessing relies on the quality of historical data, and it can take a while.
Farooq et al. [8]	SVM, DT, NB, KNN, Federated Learning model	Calculated academic performance from information from several colleges	Encourages data privacy and skillfully incorporates learning data	Federated learning setup complexity and inconsistent data quality throughout institutions
Srimani et al. [19]	Various data mining algorithms	assessed ML model performance and confirmed the learning model's efficacy	Thorough that yields precise forecasts	Results may be impacted by algorithm choice, which calls for knowledge of data mining techniques.
Agus et al [10]	EDM, LA	EDM/LA integration with strategic planning for schooling	Promotes instructional activities and supports adaptive learning	Infrastructure is needed for data integration due to implementation complexity.
Yin et al. [11]	FA-BiGRU prototype, comparison with other models	generated the most accurate estimates and was competitive in technique analysis	Improvements in forecast accuracy and the possibility of improving the education sector	Resource-intensive for training; the evaluation of the model could change based on the use case and dataset.
Sajja et al. [12]	SVM, ID3, C&RT, Random Forest	Employed data mining methods to forecast students' course achievement	discovers latent patterns in data sets and makes predictions using ML	Large datasets may need the use of powerful computing resources due to algorithm-specific biases.

Karmagatri et al. [13]	Association analysis between various factors	Examined the effects of variables (parents' qualifications, gender, etc.) on exam outcomes	Reveals strategies for preparing for exams and elements that affect academic success.	Restricted to correlations; may not prove causation
Ajibade et al. [14]	NB	Based on Bayes' Theorem, assumes feature independence.	Simple, fast, works well with large datasets, effective for categorical data.	Assumed feature independence, and struggled with highly correlated data.
	ID3	Builds a decision tree based on feature selection using information gain.	Easy to understand, interpretable, and handled both categorical and continuous data.	Prone to overfitting, sensitive to noisy data.
	SVM	Constructed a hyperplane that maximized the margin between classes.	High accuracy, effective in high-dimensional spaces, works well with a clear margin of separation.	Required careful tuning, computationally intensive for large datasets.
	k-NN	Classified data based on the majority class of nearest neighbors.	Simple, non-parametric, effective for small datasets, and adaptable for multi-class problems.	Slow for large datasets, sensitive to irrelevant features and noisy data.

3 Methodology

The passes through the data collections of children and the data is preprocessed with a Min-Max normalization algorithm, then open source software WEKA is approached for assessment of generated predictive models accuracy and followed with FSOA-KNN as a proposed model to predict children's learning effectiveness with the parameters of accuracy has measures overall correctness of predictions across all outcomes, precision has measures true positive predictions compared to all positive predictions, recall measures true positive predictions compared to actual positive cases and F-measure has balances precision and recall to give harmonic mean score of the predictive model. Figure 1 illustrates the overview of the methodology.

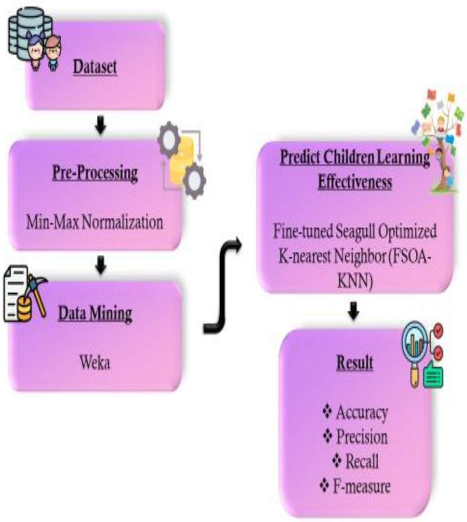

Figure1: Overview of methodology

3.1 Dataset

On the sample selection for children's learning effectiveness. Only the fields necessary for data mining were chosen in this step. A few variables that were derived were chosen. However, some data for the variables was taken straight out of the database. The data collection of around 300 students was initially gathered, all the predictor and response variables as shown in Table 2.

Table 2: Dataset description

Variable	Narrative	Value
Sex	Student sex	Male – 150 Female-150
SG	Student grades	O – 90% -80%, A – 79% - 60%, B – 59% - 40%, C – below 40%,
Fsize	Size of student's family	1, 2, 3, >3
Fstat	Familial status of students	Joint or individual family
FAR	Family Annual revenue	High, average, or poor
Pqual	Parents' qualifications	Educated (schooling grade), uneducated, or well-educated (> 1 degree)
FP	Father's Profession	Government employer, businessman, or Day laborer
MP	Mother Profession	Homemakers or working women.

d as upcoming points:

HSG: High School Grades - Students' academic progress. State board students take six courses totaling 100 marks. All students receive their grades using O is 90% to 80%, A is 79% to 60%, B is 59% to 40%, and C is below 40%.In the mapping that follows.

SG: Student's grade in primary schooling. State board students take five subjects totaling 100 points each. Every student has a grade assigned to them.

FSize: Family size is more than the number of members in the family; it's a representation of the complexities of resource allocation, interpersonal dynamics, and familial dynamics that shape people's values and goals.

FStat: Family status is more than a picture; it tells a story about the ups and downs of support systems in the family, overcoming hardship, and how socioeconomic status affects educational outcomes.

FAR: Family annual income is a compass that shows the path of economic possibilities and limitations, affecting social mobility, access to high-quality healthcare, and education.

3.2 Preprocessing

3.2.1 Min-Max normalization

The min-max normalization was a data scaling technique has transforms values to predefined range, preserving relationships within the original data. It uses minimum and maximum values to rescale data between specified boundaries, ensuring consistent comparisons. It is a technique that keeps the original data's associations intact. It is a straightforward method which able to precisely organize the data into a predetermined border using a preset boundary. The data set of students from different schools was preprocessed by Min-Max normalization, a process that uses concepts like mean and standard deviation to produce the range or normalized values of data from the original unstructured data.

$$B' = \left(\frac{B - \min\ value\ of\ B}{\max value\ of\ B - \min\ value\ of\ B}\right) * (C - D) + D \quad (1)$$

Where:

- $B'$is the normalized value.
- B is the original data value.
- $\min\ value\ of\ B$ is the minimum value of the dataset B.
- $\max value\ of\ B$ is the maximum value of the dataset B.
- C is the upper boundary of the desired range.
- D is the lower boundary of the desired range.

3.3 Implementation of mining model

Weka is an open-source program used in data mining applications that carries out a vast array of ML methods. WEKA Explorer was used to load this file. The classify panel allows the user to visualize incorrect predictions or the model itself, estimate the accuracy of a generated predictive model, and apply classification techniques, such as Fine-tuned Seagull Optimized Weighted KNN, to the resulting dataset.

3.4 FSOA-KNN

The FSOA-KNN hybrid model is designed to predict children's learning effectiveness using data mining technology. By combining Seagull Optimization with K-NN, this model optimizes the weight assignments for KNN, enhancing prediction accuracy. The fine-tuning process refines the optimization parameters, ensuring more precise and reliable predictions. This approach leverages various educational data, including performance metrics and learning behaviors, to assess and predict the effectiveness of learning methods for individual children. Algorithm 1 shows the pseudo-code of FSOA-KNN.

Algorithm 1: FSOA-KNN

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.neighbors import KNeighborsClassifier
def objective_function(params, X_train, y_train, X_val, y_val):
  k = int(params[0])
  distance_metric = params[1]
  if k < 1:
    return float('inf')
    knn = KNeighborsClassifier(n_neighbors =
k, metric = distance_metric)
  knn.fit(X_train, y_train)
    y_pred = knn.predict(X_val)
  accuracy = accuracy_score(y_val, y_pred)
    return 1 – accuracy
def firefly_swarm_optimization(X_train, y_train, X_val, y_val, max_iter, swarm_size):
    swarm = np.random.rand(swarm_size, 2)
  swarm[:, 0] = swarm[:, 0] * 19 + 1
  swarm[:, 1] =
np.random.choice(['euclidean', 'manhattan'], size =
swarm_size)
  light_intensity = np.zeros(swarm_size)
  for i in range(swarm_size):
    light_intensity[i] =
objective_function(swarm[i], X_train, y_train, X_val, y_val)
  for iteration in range(max_iter):
    for i in range(swarm_size):
      for j in range(swarm_size):
        if light_intensity[j] < light_intensity[i]:
                    swarm[i, 0] = swarm[i, 0] +
np.random.rand() * (swarm[j, 0] − swarm[i, 0])
          swarm[i, 0] =
max(1, min(20, swarm[i, 0]))
    for i in range(swarm_size):
      light_intensity[i] =
objective_function(swarm[i], X_train, y_train, X_val, y_val)
  best_index = np.argmin(light_intensity)
  return swarm[best_index]
data =
pd.read_csv("children_learning_data.csv")
X = data.drop(columns = ["target"])
y = data["target"]
X = (X − X.mean()) / X.std()
X_train, X_temp, y_train, y_temp =
train_test_split(X, y, test_size =
0.3, random_state = 42)
X_val, X_test, y_val, y_test =
train_test_split(X_temp, y_temp, test_size =
0.5, random_state = 42)
best_params =
firefly_swarm_optimization(X_train, y_train, X_val, y_val, max
50, swarm_size = 20)
best_k = int(best_params[0])
best_metric = best_params[1]
knn = KNeighborsClassifier(n_neighbors =
best_k, metric = best_metric)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Final Model Accuracy: {accuracy *
100:.2f}%")
```

3.5 Prediction of children's learning effectiveness

In this section, we predict the children's learning effectiveness using Fine-tuned seagull-optimized weighted KNN. The novelty of using a Fine-tuned Seagull Optimization Algorithm in conjunction with Weighted K-Nearest Neighbours lies in the dual process of selecting the best features and determining the optimal weights for classification. This hybrid method improves the predictive performance of making a useful tool for teachers and successfully raising student learning outcomes.

3.5.1 K-nearest neighbour

The neural network algorithm is one of the most basic and traditional methods of classification. As computing power has increased, it has gained importance and emerged as one of the most often-used categorization strategies. Because of its distance-based methodology, NN is more appropriate for use with numerical datasets with categorical datasets. The query is allocated to the class label of the point in the training set that is closest to the query, as determined by applying the fundamental logic of neural networks to the algorithm training set. The query is included in a class based on the majority of tags of the closest k-neighbour in KNN, which is an extension of NN. The Euclidian distance calculation is the most well-known.

$$Euclidean_{j,i} = \sqrt{\sum_{l=1}^{m}\left(w_{jl} - w_{il}\right)^2} \quad (2)$$

3.5.2 Weighted K- nearest neighbour

The W-KNN algorithm was initially presented by using the distance-weight function; close neighbors in the W-KNN are given a higher weight than their distant neighbors. The following Equation displays the x_j'weight of the MM in query w' in iteration j. The class to which the query will be assigned is then chosen by voting based on the l value, which determines the class label. The neighbor with the shortest distance is given more weight than the one with a greater distance. If the weights of the closest and furthest neighbors are 1, and 0, respectively, then the remaining neighbors' weights are scaled linearly based on their separation from one another.

$$x\_j\text{^}' = \{■((c(w\text{^}', w\_l\text{^}MM) - c(w\text{^}', w\_j\text{^}MM))/(c(w\text{^}', w\_l\text{^}MM) - c(w\text{^}', w\_J\text{^}MM)), if\ c(w\text{^}', w\_l\text{^}MM) \neq c(w\text{^}', w\_J\text{^}MM)@ \quad if\ c(w\text{^}', w\_l\text{^}MM) = c(w\text{^}', w\_J\text{^}MM))\} \tag{3}$$

3.5.3 Fine-tuned Seagull Optimization Algorithm (FSOA)

The benefits of the SOA method are its quick convergence speed, low computational cost, and ability to solve large-scale constrained problems. It has a lot of advantages over other optimization algorithms. The equation illustrates that the global optimization search process of SOA is linear. The global search capacity of SOA cannot be fully leveraged due to this linear search strategy. As a result, we provide a nonlinear search control formula, represented by Equation, which can enhance the algorithm's speed and accuracy by focusing on the stage of the seagull group exploration process. Figure 2 Display the flow of the Fine-tuned Seagull Optimization Algorithm (FSOA)

$$B = e_d \times \frac{1}{f^{4.\left(\frac{s}{Max_{iteration}}\right)^4}} \tag{4}$$

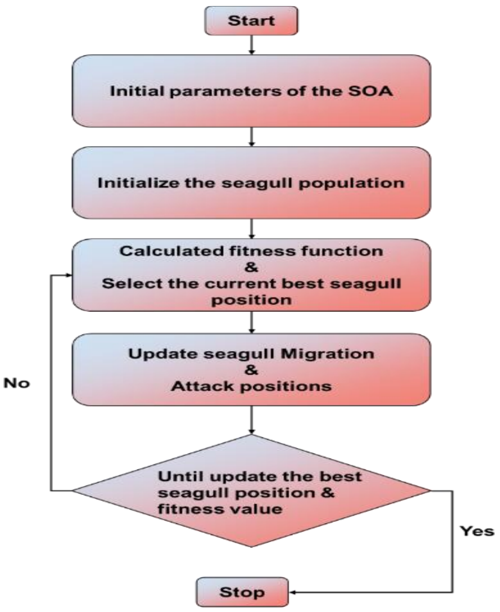

Figure2: Flow of Fine-tuned Seagull Optimization Algorithm (FSOA)

3.5.4 Fine-Tuned Seagull-Optimized Weighted KNN Algorithm

We accurately predict children's learning effectiveness by utilizing a perfectly calibrated Fine-tuned Seagull-optimized weighted KNN algorithm, allowing customized teaching tactics for the best possible results. In this case, KNN lays the foundation by offering a baseline classification or regression framework. Next WKNN enhances the procedure by assigning weighted effects to neighbouring data points. FSOA then adjusts the parameters of the hybrid model to maximize its performance on a variety of datasets. The best features of FSOA, WKNN, and NKNN are combined to create the hybrid approach, a symbiotic fusion designed to maximize the capability of each constituent algorithm. Combining this method meets better unique learning requirements of every student while optimizing academic achievement.

The proposed FSOA was based on the migratory behaviour of seagulls and their assault prey. The coding of this algorithm was inspired by the tactics used by a flock of migrating seagulls to catch their meal as they fly from one location to another. To prevent searching agents from colliding with each other in FSOA, an extra parameter "N" is used to determine the new search agent's position. The used this approach for the learning effectiveness ($\vec{F_s}$) given as

$$\vec{F_s} = \mathrm{P}x\vec{\mathrm{M}}_s(i) \tag{5}$$

$\vec{M_s}$ represents the seagull's present role, and “t” denotes the learning effectiveness iteration at that time. It is possible to model the crash prevention parameter "P" as

$$P = E_c - \left(i * (F_c/\max \cdot Iter)\right) \tag{6}$$

Here, our collision avoidance parameter is a sequentially reductive attribute from F_c to 0, which we set to 2. Using the following equation, the search agents try to approach the ideal student position once the avoidance occurrences in the collision mechanism are finished.

$$\vec{N_s} = Ax(\vec{P_{bs}}(\mathrm{i}) - \vec{M_s}(\mathrm{i})) \tag{7}$$

To attain the propensity of equilibrium between the phases of exploitation and exploration, the parameter "P" is randomly assigned and can be computed as

$$P = N^2 * 2 * \mathrm{rand}() \tag{8}$$

Subsequently, the following positions of each iteration of the algorithm will be updated:

$$\vec{R_s} = \left|\vec{\mathrm{E}}_s + \vec{N_s}\right| \tag{9}$$

While migrating, seagulls frequently modify their frequency and targeting angle based on past experiences. Seagull migration behavior can be visualized in three dimensions as

$$s' = x * \mathrm{Cos}(j) \tag{10}$$

$$T' = x * \mathrm{Sin}(j) \tag{11}$$

$$U' = x * \mathrm{j} \tag{12}$$

The spiral movement radius of the seagulls is represented by "x", and an element between 0 and 2 is chosen at random for "j". The remaining agents in the search will have their positions updated in accordance with the optimal solution once it has been saved.

$$\vec{M_s}(k) = \left(\vec{N_s} * s' * T' * U'\right) + \vec{P_{bs}}(k) \tag{13}$$

A graphic illustration of the steps involved in FSOA optimization is shown in Figure 2. Although FSOA has been successfully used for other technical optimization problems, the authors are not aware of any literature that reports on its application to learning optimization problems. The clever behaviour of seagulls motivated the authors to employ the FSOA searching approach for the learning behaviour.

4 Result analysis

Our suggested method was carried out using an Intel i5 8th Gen laptop running Windows 11 with 32 GB of RAM and an environment for Python 3.10.1. To evaluate children's learning using a range of measures were recall, precision, F-Measure and accuracy. Existing methods such as SVM, NB, ID3, and KNN [15].

Accuracy analyzes the proportion of incidents that are consistently classified efficiently. The FSOA-KNN model demonstrates high accuracy in predicting children's learning effectiveness. By leveraging Seagull Optimization for fine-tuning and integrating weighted KNN, it improves classification precision, adapting to various learning patterns. In studies, this model has shown superior performance, offering reliable predictions with a significant reduction in error rates compared to traditional methods. Figure 3 and Table 3 illustrate the result of the accuracy. Compared to the existing method NB (79.2%), ID3 (95.1%), SVM (91.8%), and KNN (96.8%) Our proposed method was higher FSO-WKNN (97%). The proposed approach, FSO-WKNN, has significantly improved children's learning effectiveness prediction when compared to current methods.

Table 3: Outcome value of accuracy

Method	Accuracy (%)
NB [15]	79.2
ID3 [15]	95.1
SVM [15]	91.8
KNN [15]	96.8
FSO-WKNN [Proposed]	97

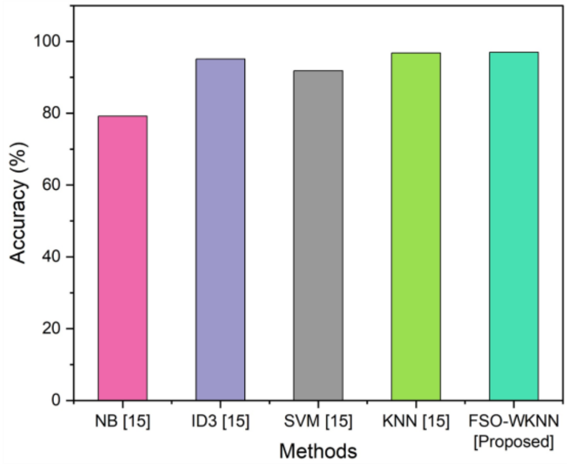

Figure 3: Outcome Of accuracy

Precision shows the percentage of accurate, well-made forecasts among all predicted events. The FSOA-KNN model demonstrates high precision in predicting children’s learning effectiveness by leveraging data mining technology. Its optimization through the Seagull algorithm enhances the KNN's ability to accurately classify learning outcomes, offering improved performance over traditional KNN. The model adapts to various educational contexts, providing reliable predictions of student progress and effectiveness. Figure 4 and Table 4 illustrate the result of the precision. Compared to the existing method NB (77.6%), ID3 (94.6%), SVM (90%), and KNN (95.5%) Our proposed method was higher FSO-WKNN (96.5%). The proposed approach, FSO-WKNN, has significantly improved children's learning effectiveness prediction when compared to current methods.

Table 4: Represent the precision comparison values

Method	Precision (%)
NB [15]	77.6
ID3 [15]	94.6
SVM [15]	90
KNN [15]	95.5
FSO-WKNN [Proposed]	96.5

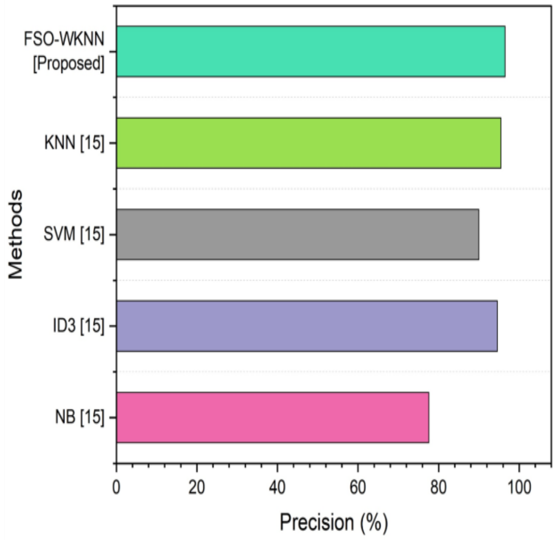

Figure 4: Outcome of precision

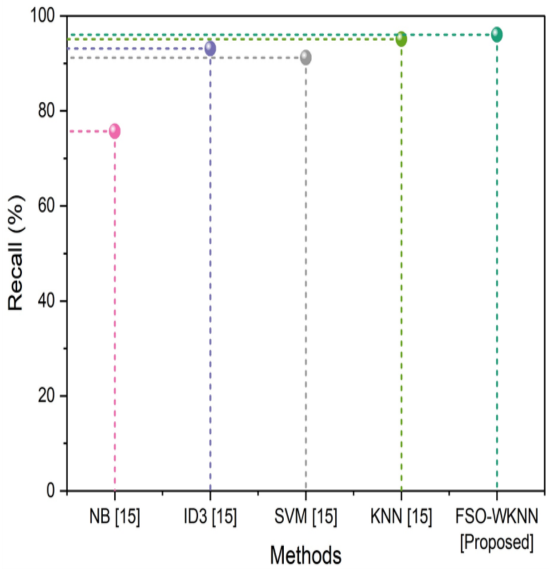

Figure 5: Outcome of recall

Recalls show the percentage of true positives that are effectively acknowledged out of all real positives. The FSOA-KNN is a data mining model used to predict children's learning effectiveness. By combining Seagull Optimization with KNN, the model fine-tunes feature weights to improve prediction accuracy. It utilizes a data-driven approach to assess factors influencing learning outcomes, offering valuable insights into educational interventions and personalized learning strategies. Figure 5 and Table 5 illustrate the result of the recall. Compared to the existing method NB (75.7%), ID3 (93.1%), SVM (91.2%), and KNN (95.1%) Our proposed method was higher FSO-WKNN (96%). The proposed approach, FSO-WKNN, has significantly improved children's learning effectiveness prediction when compared to current methods.

Table 5: Represent the recall comparison value

Method	**Recall (%)**
NB [15]	75.7
ID3 [15]	93.1
SVM [15]	91.2
KNN [15]	95.1
FSO-WKNN [Proposed]	96

F-measure is the precision and recall harmonic average that balances the two measurements and is especially useful for unbalanced datasets. The F-measure of the FSOA-KNN for predicting children's learning effectiveness using data mining technology evaluates the model's balance between precision and recall. A higher F-measure indicates better predictive performance, demonstrating FSOA-KNN's effectiveness in accurately classifying children's learning outcomes. Optimizing the KNN algorithm with Seagull optimization enhances its overall predictive accuracy. Figure 6 and table 6 illustrate the result of the F-Measure. Compared to the existing method NB (75.1%), ID3 (91.3%), SVM (86.8%), and KNN (94.6%) Our proposed method was higher FSO-WKNN (95.5%). The proposed approach, FSO-WKNN, has significantly improved children's learning effectiveness prediction when compared to current methods.

Table 6: Comparisons Of F-measure values

Method	**F-Measure (%)**
NB [15]	75.1
ID3[15]	91.3
SVM [15]	86.8
KNN [15]	94.6
FSO-WKNN [Proposed]	95.5

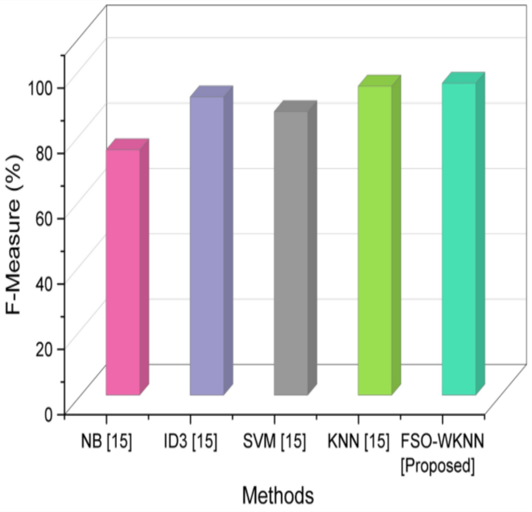

Figure 6: Outcome of F-Measure

4.1 Discussion

The performance comparison of various ML methods reveals that the proposed FSO-WKNN model outperforms traditional methods across all evaluation metrics, including accuracy, precision, recall, and F-measure. The accuracy of the FSO-WKNN model is 97%, surpassing KNN (96.8%), SVM (91.8%), ID3 (95.1%), and NB (79.2%). Similarly, the precision of FSO-WKNN at 96.5% is higher than KNN (95.5%) and significantly better than other models. In terms of recall, FSO-WKNN achieves 96%, leading over KNN (95.1%), SVM (91.2%), ID3 (93.1%), and NB (75.7%). The F-measure, which balances precision and recall, also reflects FSO-WKNN's superior performance, with a value of 95.5%, compared to KNN (94.6%), SVM (86.8%), ID3 (91.3%), and NB (75.1%). This consistent superiority across all metrics suggests that the FSO-WKNN model effectively enhances classification performance, making it a promising solution for the task at hand.

5 Conclusion

Prediction of children's learning effectiveness entails evaluating elements such as cognitive capacity, socioeconomic background, teaching techniques, and individual attributes. The uses data mining technologies to present a novel method for predicting children's learning effectiveness: FSOA-KNN. Using pre-processing we are able to anticipate learning efficiency with greater accuracy than previous approaches by utilizing the data collected from 300 students. The experimental results display that the suggested strategy is effective, outperforming conventional methods in phrases of accuracy (97%), precision (96.5%), recall (96%), and F-Measure (95.5%). This research improves educational practices and promotes improved learning outcomes. When working with huge datasets, the FSOA-KNN algorithm's computational complexity may cause scalability problems. The size of the dataset may affect the amount of time and money required for training and prediction. To improve prediction accuracy and applicability in a variety of educational settings, future developments may incorporate deep learning techniques to improve feature representation and scalability.

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