International Journal of Computational and Experimental Science and ENgineering
(IJCESEN)

Vol. 11-No.1 (2025) pp. 974-989
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

Student Interest Performance Prediction Based on Improved Decision Support Vector Regression Using Machine Learning

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Article Info:

DOI: 10.22399/ijcesen.999
Received : 25 November 2024
Accepted : 02 February 2025

Keywords :

Machine Learning,
Student Performance Prediction,
IDSVR,
LKHOA,
PLMA,
FFLB and classification.

Abstract:

The economic success of a government relies on the capability of its citizens to afford higher education. Ensuring maximum importance is given to this case is a crucial task for any government. However, the cost of education is affected by the amount of time students study before graduation. Moreover, one of the main obstacles facing universities is analyzing performance, proposing ways to improve the quality of education, and developing strategies to evaluate future practices. However, there is a lack of effectiveness and accuracy in standards for areas such as planning, leadership, online learning, student support, and assessment. To solve this problem, we use the Improved Decision Support Vector Regression (IDSVR) method to identify and determine the degree of quality verification for training schemes. Firstly, we used the Preferred Learning Materials Acquisition (PLMA) method to assess the similarity between student's learning and s behaviors. After that, the Lion and Krill Herd Optimization Algorithm (LKHOA) can be utilized to generate an efficient method for feature extraction. Finally, the IDSVR classification system can be used to identify and evaluate the level of quality assurance implementation in training programs based on Machine Learning (ML) techniques.

1. Introduction

In recent times, student's academic performance can be assessed through memory tests and periodic examinations. Additionally, analyzing students' scores enables us to pinpoint the factors that forecast academic achievements. Moreover, student performance ratings reflect the significance of educational institutions responsible for educating individuals at different stages of life. It can analyze the knowledge provided by other educational data sources and extract the required information. Furthermore, Educational Data Mining (EDM) techniques can be utilized to generate and discover valuable information [1,2].

In addition, large amounts of data can be generated, and students can interact with learning platforms and materials. Moreover, analyzing data can provide insight into student learning processes and student outcomes. Furthermore, student performance can be analyzed to identify academic, demographic, and social factors that impact academic success. The importance of EMD is evident when considering the rise of conventional educational methods and different e-learning approaches that have resulted in a significant surge in the amount of educational data being produced. Additionally, students' performance in different subjects can be evaluated to determine their academic achievements [3]. However, higher education institutions are currently more likely to face the difficult task of attracting students to meet various educational needs effectively. In addition to these needs, it can be challenging to develop strategies to improve the learning experience of students. However, predicting academic performance remains a challenge for many educational institutions such as data centres, schools, colleges, and universities. The impact of digital educational technologies on student's cognitive skills still needs to be determined despite the controversy. Currently, there is no consensus on the cognitive impact of these technologies on secondary school students. However, it is important to consider the heterogeneity of this effect and the uncertainty in occupation, which cannot be reduced [4,5].

The contribution of this section is that, first, we use a student performance prediction dataset obtained from the Kaggle repository to predict student interest. Furthermore, we use the PLMA method to assess the similarity of student learning behaviors. Additionally, LKHOA can be used to develop more efficient feature extraction methods. Furthermore, a more effective feature set can be achieved by selecting features using the FFLB method and evaluating their importance to student's learning behaviors.

Finally, the ML-based IDSVR classification method can be used to identify and evaluate the level of quality assurance performance in training program activities. As presented in Figure 1, we propose a basic architectural diagram to discover performance predictor scores for students of interest.

Moreover, to predict these accuracies, quality measurement can be achieved by collecting human data from the dataset and evaluating student behavior based on methods, feature extraction, feature selection, and classification.

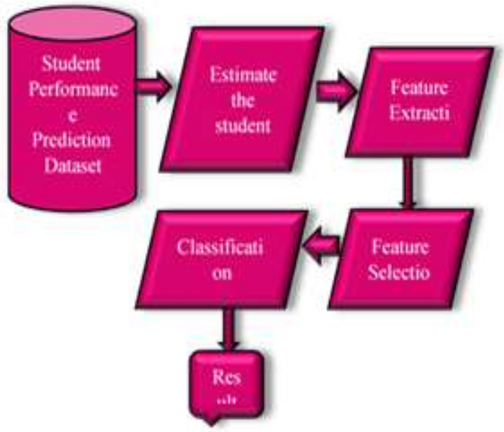


Figure 1. *The Basic Architecture Diagram for Student Performance Prediction*

2. Literature Survey

The author [6] suggested that measuring the achievement of learning outcomes can be done through standards and achievement scores. However, studies on predictors of student performance still need to be completed. After that EDM techniques can be implemented to provide an assessment of student classroom performance. However, the previous experiment did not adequately observe the temporal aspect of prediction [7]. Similarly, the predictive effectiveness of powerful artificial intelligence (AI) methodology is predicted to elucidate the relationships between student learning factors and create effective education and learning interventions [8]. According to the Preference Cognitive Diagnosis (PCD) model to determine students' knowledge levels, Traditional cognitive diagnoses lack accuracy, and joint filtering predictions are not easily interpretable [9]. Weighted scores (WS) can be used to predict both parametric and non-parametric D-vine copula models from test score results [10]. It was proposed developing a multiple regression model to enhance the accuracy of predicting learner's academic performance for measuring their future performance in other courses [11]. The default strategy of the strategy of the Synthetic Minority Oversampling Technique (SMOTE) can be implemented, which is to overestimate all classes using the sample size of the majority class [12]. Absolute grades can be predicted based on the implementation of a learning management system (LMS) through enrolment activities for interested students using DL-based learning analytics [13]. Similarly, Genetic algorithm (GA) techniques based on feature selection can be used to predict student's academic ability [14]. Furthermore, data mining techniques can be enforced to support college access decisions and predict the performance of college applicants [15]. The measurement accuracy and explanatory power can be assessed by analyzing additional tests of student achievement prediction models [16]. After that, the Neural Network (NN) technique is used to predict the academic performance of students based on their characteristics. Additionally, interpretive AI technology could be utilized to identify predictive variables [17]. Similarly, innovative uses of the Neutrosophic Set (NS) approach to completely estimate the cognitive level of student's learning concepts from three factors: the extent of understanding, misunderstanding, and uncertainty [18]. In addition, improving K-means by incorporating unused statistics to enhance cluster results [19]. That evaluating the Augmented Education (AE) model could provide a more precise prediction of student academic achievement [20]. It was proposed a generalized Exercise-Enhanced Recurrent NN (EERNN) framework by analyzing student recordings and movements [21]. Likewise, they deal with a multi-source sparse attentional CNN (MSACNN) method to predict object ratings using a general approach [22]. After that, Different Deep Learning (DL) methods could be utilized to predict student performance. However, these approaches have shown limited effectiveness in reducing formal warnings and removals from universities [23]. To solve the above problem, an improved Conditional Generative Adversarial Network Deep SVM (ICGAN-DSVM) algorithm was used to predict student performance through school and teacher-assisted learning [24]. Similarly, that more investigation could be performed in the field of education utilizing various ML techniques to manage the problem of student orientation and performance [25]. Additionally, a Multi-Layer Adaptive Neuro Fuzzy Inference System (MANFIS) can predict student performance in online higher education settings [26]. That educational method could be enhanced in order to advance the EDM research field by enabling the utilization of data knowledge [27]. Similarly, the Grade Point Average (GPA) system is utilized as a means of forecasting a student's likelihood of failing a course within a given semester [28]. Furthermore, by using different evaluation metrics, such as reducing the number of classes and modelling nominal features, improved performance can be predicted [29]. Likewise, they implement a three-branch convolutional neural network (CNN) framework to predict curvature and focus functions across rows, columns, and depths [30]. Table 1 underlines the various techniques and issues involved in finding predictors of student performance of interest based on ML. They presented using DL techniques to forecast learner's academic performance and analyze their implementation in educational data mining to specify at-risk students [31]. It was suggested that dynamic testing based on predictive measures can be submitted to introduce personalization to student learning [32]. Learning-generated data can be analyzed by implementing an Explainable Learning Analysis (ELA) methodology based on a hybrid learning model derived from a technical university [33]. A student's final-semester grades using the Doctor of Veterinary Medicine (DVM) system can be used to determine prior academic records, statistics, and first-semester grades [34]. After that, the Harris-Hawkes Optimization (HHO) algorithm is implemented, and a modified performance is used to control population heterogeneity. These services solve the early convergence problem and prevent falling into local optima [35].

3. Proposed Methodology

We utilise the Student Performance Prediction dataset collected from the Kaggle repository to determine the grade-level performance of interested students. Furthermore, the PLMA technique is used to assess the similarity of student learning behaviors. This method involves systematizing teaching materials and students and calculating similarities between them. Furthermore, the LKHOA method can be used to develop highly efficient feature extraction methods, which involve converting raw data into processable digital features while preserving the information in the original dataset. Moreover, a more effective feature set can be obtained by selecting features using the FFLB method and assessing their importance to student's learning behavior. The ML-based IDSVR classification system can identify quality assurance student interest and assess performance levels in training program activities. The IDSVR framework of the proposed method can be seen as introduced in Figure 2. It is utilized to specify and evaluate grade assurance performance levels in training program movements. Furthermore, techniques can be devised to extract data from the initial dataset by analyzing the similarity of student's learning behaviors. Subsequently, the effectiveness of the training program can be assessed based on the student's learning behavior.

3.1 Dataset Collection

We use the Student Performance Prediction dataset collected from the Kaggle repository to determine the grade-level performance of interested students. Furthermore, predictions for students interested are foundathttps://www.kaggle.com/datasets/prajwalka nade/student-performance-prediction-dataset.s In addition, it has become a valuable resource for understanding and enhancing student achievement. Furthermore, the Kaggle is a valuable platform for creating predictive models and analyzing factors that contribute to student success using datasets. Educators and policymakers can use the insights gained from the data set to work and improve student educational experiences and outcomes. Also, a comprehensive set of structured data can facilitate predictive analytics related to student academic performance. This student performance prediction dataset is invaluable to educators, students, and data scientists examining for insights into the elements that impact student success. It permits the creation of predictive models, identifies key factors affecting student outcomes, and enables informed decisions to improve education. In addition, attributes provide a complete view of each student's academic and personal profile. Furthermore, they offer predictive modelling to enable datasets for various analyses, identifying influencing factors and evaluating student performance. Students interested in education can use data on factors that contribute to success and challenges to researchers and educators to gain insights into interactions. Based on a comprehensive analysis of each student's academic and personal profile, these attributes are assigned as shown in Figure 3. In addition, student performance can be predicted through insights gained from the data. Moreover, the target dataset for student performance contains 149 records, and there are 15 features available to predict student performance. Table 2 shows student performance prediction attribute dataset description.

3.2 Preferred Learning Materials Acquisition (PLMA)

The similarity of student's learning behaviors can be assessed using the PLMA method. Furthermore, the PLMA method involves organizing variables, evaluating their similarity, and primarily computing the learning objects. Moreover, using the PLMA technique, it is possible to implicitly analyze the similarity of student's learning behaviors while studying learning materials. Students can acquire learning materials through the PLMA method, which combines direct and indirect strategies. This PLMA method also assists students in studying the procedures they need or want to learn while engaging with the learning materials. In addition, the PLMA method usually incorporates a wealth of information about student preferences in learning materials. Moreover, the PLMA method enables the organization of learning materials by keyword and topic dimensions. Frequently, students with similar learning behaviors may have similar preferences for learning materials. Therefore, the PLMA technique can be identified by analyzing the similarities in learning behaviors among interested students. Calculate the similarity between the student and the learning object, as shown in Equation 1. Let's assume K^q −learning material, L_q −keuword vector, M_q −topic distribution vector.

$$K^q = \{L_q; M_q\} \tag{1}$$

Calculate the relative weights of the keyword and topic distribution vectors as shown in Equation 2 and 3. Let's assume the L-keyword, Z-weight, and v-vector.

$$l_q = \{(L_q^1, Z_q^1), (L_q^2, Z_q^2), \dots\} \tag{2}$$

$$M_q = \{(M_q^1, y_q^1), (M_q^2, y_q^2), \dots\} \tag{3}$$

Calculate the weight of the keyword as shown in Equation 4. Let's assume Z_{xq}^b −corresponding weight, σ_x^b −Keyword, H_x^b −formalize student vector, D_x −reading conten

$$\sigma_x^b = \frac{\sum_{H_x^b \in K_{un,n=1}}^{|D_x|} Z_{xq}^b}{|p|} \tag{4}$$
$$M = \{H_x^b | H_x^b \in L_{x,q=1}, \dots, |D_x|\}$$

As shown in Equation 5, calculate the student's weights on the topics related to their reading content. Let's assume μ_x^b −topic of student weight, Y_{xq}^b −corresponding weight vector

$$\mu_x^b = \frac{\sum_{q=1}^{|D_x|} Y_{zq}^b}{|D_x|} \tag{5}$$

To determine the student's preference for learning materials, use Equations 6 to 8. Where C_{xq}^M −degree preferred, $\rho\ and\ \mu$ −weight parameter, t-similarity, E_x −reading vector topic, S-reading time, T^x −preference degree student, H-keyword vector, E-topic distribution vector.

$$C_{xq}^M = \mathscr{s}_{\mathbb{im}}[T^x, K^q] = \frac{\rho^t(h_x, L_q) + (1-\rho)T(E_x, M_q)}{\sqrt{\rho^2 + (1+\rho)^2}} \tag{6}$$

$$(H_x, K_q) = \frac{\sum_{a=1}^{T}(\sigma_x^a \times Z_{xq}^a)}{\sqrt{\sum_{a=1}^{S}(\sigma_x^a)^2} \times \sqrt{\sum_{a=1}^{s}(Z_{xq}^a)^2}} \tag{7}$$

$$(E_x, M_q) = \frac{\sum_{a=1}^{F}(\mu_q^a \times Y_{xq}^a)}{\sqrt{\sum_{a=1}^{F}(\mu_x^a)^2} \times \sqrt{\sum_{a=1}^{F}(Y_{xq}^a)^2}} \tag{8}$$

Calculate the similarity of student's learning behaviors as described in equation 9. Let's assume

$the\ S_{xq}$ −reading time of student, $K_x^q\ and\ Aq_x^b$ −interaction between learning material, C_j, −proportion of the number of elements, $C_u \cap C_j$ −small and large student material.

$$tp^{x_b} = \frac{\sum_{K_x^q \in Aq_x^b, q=1}^{|D_x|} S_{xq}}{\sum_{n=1}^{|C_u|} t_{un}} \times \mu,\ Aq_x^b = D_x \cap D_b,\ \mu = \frac{|Aq_x^b|}{|D_{b'}|} \quad (9)$$

Compute student's implicit preferences for the learning course as shown in Equations 10 and 11. Let's assume $\mathbb{m}_{ax}$ −denote maximum value, $a_{xq}^m and\ R_{xq}^a$ −indirect preference degree of the student.

$$a_{xq}^m = \mathbb{m}_{ax}\left(R_{xq}^1, R_{xq}^2, \ldots, R_{xq}^b\right) \quad (10)$$

$$R_{xq}^a = tp_{x^a} \times Cm_{q^a}, \quad a = 1,2,..,b \quad (11)$$

Formalized students with high direct and indirect preferences can have learning materials selected using the PLMA system. Figure 4 depicts direct and indirect methods for acquiring data to support and predict student performance while studying learning materials, as well as providing information on the student's overall preferences for said materials.

3.3 Lion and Krill Herd Optimization Algorithm (LKHOA)

In this section, we create a feature extraction method for learners using LKHOA to improve learning performance effectively. Additionally, the LKHOA method, which is based on feature extraction, maintains the information in the original dataset and facilitates the transformation of raw data into digital features that can be processed. The LKHOA method utilizes matching features to optimize, allocating time to optimize each selected set from different methods uniformly. In addition, the initial population of lions consists of randomly generated solutions. Some of the lions were selected as nomadic lions, while the remaining lions were divided into sub-groups called prides. The lion's behaviour, such as hunting, flight for protection, wandering, breeding, migration, conservation, population stability, and aggregation, can be simulated using LKHOA techniques, which are based on the behaviour of lions. The LKHOA approach utilized to generate the population produces a completely arbitrary solution for lions. The LKHOA algorithm is a unique type of swarm intelligence enhancement that is based on simulating individual krill behavioural deviations and a combination of environmental and biological phenomena. In this LKHOA algorithm, each individual in a krill swarm contributes to the migration process according to its performance, simulating the behavior of a krill. The LKHOA method can be used to evaluate the capability to extract features and generate optimization techniques for interested students. Calculate the uniform or multimodal constant surface initial population as shown in Equation 12. Let's assume the o-optimal, U_a^{min}, U_a^{max} −optimization procedure, I −argument, h-unction, and U-argument vector

$$U^r = I \underset{U_a(U_a^{min}, U_a^{max}}{min} h\left(u_1, u_2, .., u_q\right); q \geq 1 \quad (12)$$

The size of the solution region can be calculated as described in Equation 13. Let's assume P-model, a-variable,

$$P_q = \prod_{a=1}^{q}(\ U_a^{min} -\ U_a^{max}) \quad (13)$$

Compute the actual solution for the size optimization as shown in Equation 14. Let's assume k-lion, i-value, i^{K_y} −dimensional optimization.

$$K = [i^1, i^2, .., i^{K_y}] \quad (14)$$

The cost function to calculate the fitness value of each lion is illustrated in Equation 15. Let's assume f-fitness value.

$$h_y^k = H^K[i^1, i^2, .., i^{K_y}] \quad (15)$$

As shown in Equation 16, calculate the success of the lion by iteratively optimizing its position. Let's assume T^y −success value, C-Iteration, E-group, K-lion, J-best value, $J_C^{K,e}$ −best position.

$$T^y\{K, C, E\} = \begin{cases} 1J_c^{K,E} < J_{c-1}^{K,E} \\ 1J_c^{K,E} = J_{c-1}^{K,E} \end{cases} \quad (16)$$

Calculate the optimal dimensions for space exploration capacity as shown in Equation 16. Where P^v − movement caused Krill, h^v −foraging movement, V-krill, m_v −phtsical diffusing.

$$\frac{c_I^v}{c_S} = T^y(P^v + h^v + m_v) \quad (17)$$

Calculate the effect of surroundings on individual displaced krills as shown in Equation 18. Let's assume $L_{F^{worst}} - L_{F^{best}}$ −best and worst fitness level, U-fitness goal value function,

$A_{u,v}$ −individual fitness value, $L_{F^u} - L_{F^v}$ −denote fitness neighbour, I-associate coordinate, z-significant positive number, Q_q −denote number on neighbour.

$$\begin{cases} \mu_v^{Local} = \sum_{u=1}^{Q_q} \widehat{L_{F_{u,v}}} \widehat{A_{u,v}} \\ \widehat{A_{u,v}} = A^v - A^u / \|A^v - A^u\| + z \\ \widehat{L_{F_{u,v}}} = L_{F^u} - L_{F^v} / L_{F^{W_{orst}}} - L_{F^{b_{est}}} \end{cases} \quad (18)$$

The optimizations for the Krill and the Lion groups are calculated using Equation 19.

$$L_F^K = (T^y\{K, C, E\}) \frac{L_{F^u} - L_{F^v}}{F_{W_{orst}} - F_{b_{est}}} \quad (19)$$

In the context of local search, neighbour effects can be understood as patterns of attraction or repulsion for each other. It can be observed that the integrity of fit is the result of the objective function. By optimizing the extracted features using the Krill and Lion group, we can evaluate student's interest performance, as shown in Figure 5. Furthermore, it can be divided based on types of student sports activities, features based on student grade numbers, student study time statistics, and a number of feature extraction peripherals.

3.4 Filtered Feature Learning Behavior (FFLB)

The FFLB method can be used to select features and evaluate the importance of student learning behaviours, resulting in a more effective feature set. The FFLB method is a technique for identifying and describing features that enhance student performance modelling and improve its effectiveness. In addition, this FFLB method enables the selection of the most relevant features that significantly contribute to student learning during the feature selection process. The FFLB method can be manipulated to estimate the importance of reproductive behaviours. Furthermore, the distributed filter can acquire a superior feature set for filtering feature selection compared to the FFLB-based method. Using the FFLB method, a weighted combination of various measurements is utilized as the fitness value for the current solution. In addition, the total number of learning functions utilized to compute the fitness rate can be combined to reduce the dimensionality of the data. Feature selection theory can effectively improve prediction accuracy and reduce the complexity of learning decisions. Furthermore, the FFLB method can be used to provide an estimate of feature selection during training and to detect a subset of features. Calculate the number of behaviors learned by each student, as shown in Equation 20. Let's assume P- number of feature, U_a −each individual value,

$$U_a = L_F^k(U_{a^1}, U_{a^2}, U_{a^3}, \ldots, U_{a^q}), \ \ a \in [1, P] \quad (20)$$

Calculate each component of the upper and lower bounds of the solution as described in Equation 21. Where O_q −random number, K-lower bound, X-upper bound, $K_{m_{in}}$ −, lower minimum solution, U^{a_x} −upper maximum solution.

$$U_{a_b} = K_{m_{in}} O_q(0,1) \times \left(U^{a_x} - K_{m_{in}}\right) \quad (21)$$

Calculate the maximum fitness value as indicated in equation 22. Let's assume A_{cc} −accuracy, F_S −F1-score, R_c −recall, P_n −precision, and f-fitness value.

$$H = 0.3 \times A_{cc} + 0.3 \times F_S + 0.2 \times R_c + 0.1 \times P_n + 0.1 + {0.1}/{q_{feature}} \quad (22)$$

The mutational crossover strategy solution can be calculated using Equation 23. Let's assume v-cross over, g-mutation, p-population, U_m^1, U_m^2, U_m^3 −random solution.

$$Y^a(e) = U_m^1(e) + H \times \left(U_m^2(e) - U_m^3(e)\right) \quad (23)$$

Calculate the crossover strategy as depicted in equation 24. Let's assume X^{a_b}, U_a^b, $and\ Y^{a_b}$ − generate new individual performance, d^o −crossover threshold rate, and e-strategy, a and b- cross-component.

$$X^{a_b} = d\left(U_a^b(e), Y^{a_b}(e)\right), O_q(0,1) < d^o \\ U_a^b(e), \qquad else \quad (24)$$

Calculate the adaptive crossover rate for population stability, as indicated in equation 25. Let's assume the S-total number of iterations, the e-number of the current iteration, and the g-early population.

$$\lambda = g^{(1-S)/(S+1-e)} \quad (25)$$

Estimate the fitness computation from the new population as shown in Equation 26.

$$U_a(e+1) = \begin{cases} y^a(e), H\left(y^a(e)\right) > H\left(U^a(e)\right) \\ U^a(e), \qquad else \end{cases} \quad (26)$$

It enables obtaining the best feature set for feature selection and using the current best feature set as input for interest students. Important features for student learning behaviour are selected according to their fitness values and crossover rates.

Generating features to analyze the performance of the learner and obtain the optimal feature set for feature selection allows for evaluation of the new population, as shown in Figure 6.

3.5 Improved Decision Support Vector Regression (IDSVR)

The IDSVR classification system is used to identify and assess the extent to which quality assurance is implemented in student training programs of interest. The IDSVR classification method is generated by averaging the separating hyperplanes. The idea of the IDSVR method is to classify data in the background into categories by drawing lines or hyperplanes. The IDSVR method can be classified to find the best surface that separates all pairs of different data classes. As the data becomes more complex, dimensions are added to the domain to divide the data linearly. The IDSVR method consists of sub-learning techniques that can be employed for both classification and regression purposes. The weights of the IDSVR method are specified to define the student performance dynamically. In order to evaluate the learning performance of the students, the IDSVR algorithm consists of testing process parameters using decision weights for student interest. This IDSVR method represents the separation of hyperplanes produced in a discriminant classifier. In a two-dimensional space, the two classes can be separated by the hyperplane, with each class appearing on opposite sides of the hyperplane. IDSVR applies kernel methods for performing nonlinear classification. The essential concept of this kernel trick is to divide the binary classifier's data by projecting it into a feature space with a high dimension. Compute training samples for the target classifier as shown in Equation 27. Let's assume $\emptyset(i^u)$ −nonlinear function, w −weight parameter, v-bias parameter, μ^u −slack variable, L-kernel function.

$$\min_{u,v,\mu}{}^{(i,j),u=1,2,..,q}\left\{\frac{1}{2}w^t w+L\left(\sum_{U=1}^{q}\mu^u\right)\right\}=j_u\left(z^2\emptyset(i^u)+v\right) \tag{27}$$

Equation 28 is used to calculate the optimal hyperplane using the Lagrangian method. Where $the\ w_{(\alpha)}$ −quadratic equation,

$$m^{ax}z_{(\alpha)}=\sum_{u=1}^{q}\alpha^u-\frac{1}{2}\sum_{u=1}^{q}\sum_{v=1}^{q}\alpha^u\alpha^v j_u j_u\,D(i_u,i_v) \tag{28}$$

Compute the set of Lagrange multipliers and kernel functions as shown in equation 29. Where D-collection of function, $\emptyset(\alpha_u)$ −multilayer kernel function.

$$D(i^u,i^v)=\emptyset(\alpha_u)^t\emptyset(\alpha_u) \tag{29}$$

Evaluate the resultant function described in Equation 30. Where h-function, j-potentially correlated feature, n-lower dimension.

$$h(i)=\sum_{u=1}^{q}\alpha_u j_u\,D(i^u,i^v)+v \tag{30}$$

Compute the mean of the processed data for each attribute as shown in Equation 31.

$$\Upsilon=\frac{1}{p}\sum_{u=1}^{p}i_u \tag{31}$$

As shown in Equation 32, variance is calculated by examining all features in the data set. Where y-variance, I-variable,

$$(I)=\sigma_i^2=\frac{1}{p-1}\sum_{u=1}^{p}(u^u-\Upsilon)^2 \tag{32}$$

Calculate the covariance and correlation of the two variables as shown in Equation 33. Where D-covariance, I, J-two variable,

$$D_{(I,J)}=\sigma_i^2=\frac{1}{p-1}\sum_{u=1}^{p}(i^u-\Upsilon_I)\left(i^u-\Upsilon_j\right) \tag{33}$$

The diagonal of the covariance matrix represents the covariance between input variables. Furthermore, parameters are represented by variables, respectively. The IPVMIP architecture in Figure 7 utilizes the support vector method for classifying student performance based on maximum margin positive and negative hyperplane classification data.

4. Result and discussion

In this section, we first evaluate student behaviour using a dataset predicting their performance. Efficient methods can be implemented to create better features for feature extraction. Aspects can be selected by evaluating their importance and student learning behavior. Furthermore, the quality of student performance can be identified and evaluated based on classification models. When evaluating the performance of a binary classification model, different metrics can be used. These include accuracy, precision, recall, F1 score, and specificity. In binary classification, true positives represent the number of positive events predicted accurately by the model. True negatives represent the number of negative samples for which the quantification prediction was correct. False positives describe the number of examples where a positive is accurately predicted. False negatives define the number of samples that falsely predict negatives.

Precision=
$Positive^{True}/Positive^{True} + Positive^{False}$
(34)

Recall=
$Positive^{True}/Positive^{True} + Negative^{False}$ (35)

F1-
Score=$P^{precision} * Re^{call}/P^{precision} + Re^{call}$(36)

Specificity=
$Negative^{True}/Negative^{True} + Positive^{False}$
(37)

Accuracy=
$$\frac{[Positive^{True}+Negative^{True}]}{[Positive^{True}+Negative^{True}+Positive^{False}+Negative^{False}]}$$
(38)

Table 1. *Machine Learning based on Student Performance Prediction*

Author	Year	Technique	Disadvantage
S. D. A. Bujang	2021	Support Vector Machine (SVM)	However, the prediction of student grades needs to improve performance when dealing with imbalanced data sets.
M. Adnan	2021	Massive Open Online Course (MOOC)	Online learning media struggle with low attention, high dropout rates, and a lack of motivation from students.
P. Asthana	2023	ML	Although they accurately predict student performance, they do not provide indicators to enhance implementation.
Y. Shi	2023	Decision Tree, Naive Bayes	However, self-discovery and continuous education are essential criteria.
G. Latif	2023	ML	However, the growing number of students in all grades requires attention from educators.
D. Liu	2020	ML	It is common for the behavioural traits of some students to be disregarded.
S. Rai	2021	ML	Although the approach is widely used, participation is low, and turnover is high.
B. Albreiki	2021	EDM	One of the major challenges universities face is reflecting on the future.
F. Ofori	2020	ML	Analyzing student performance is difficult due to the large amount of academic data available.
F. Qiu	2022	Behaviour Classification- E-Learning Performance (BCEP)	However, it fails to consider the crucial link between behaviors in e-learning.

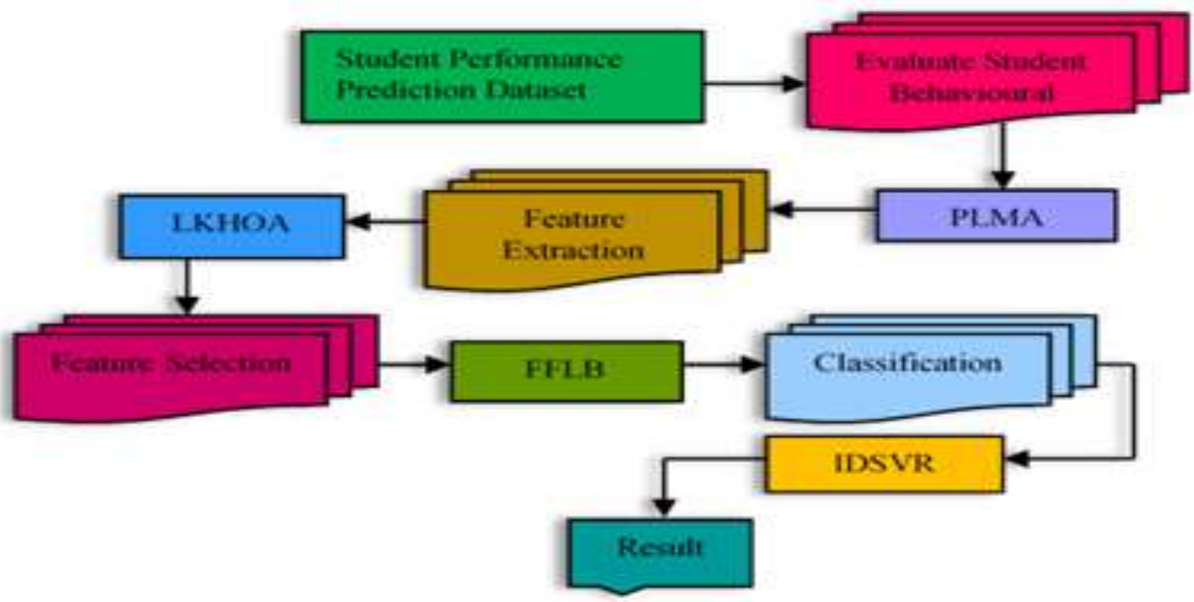


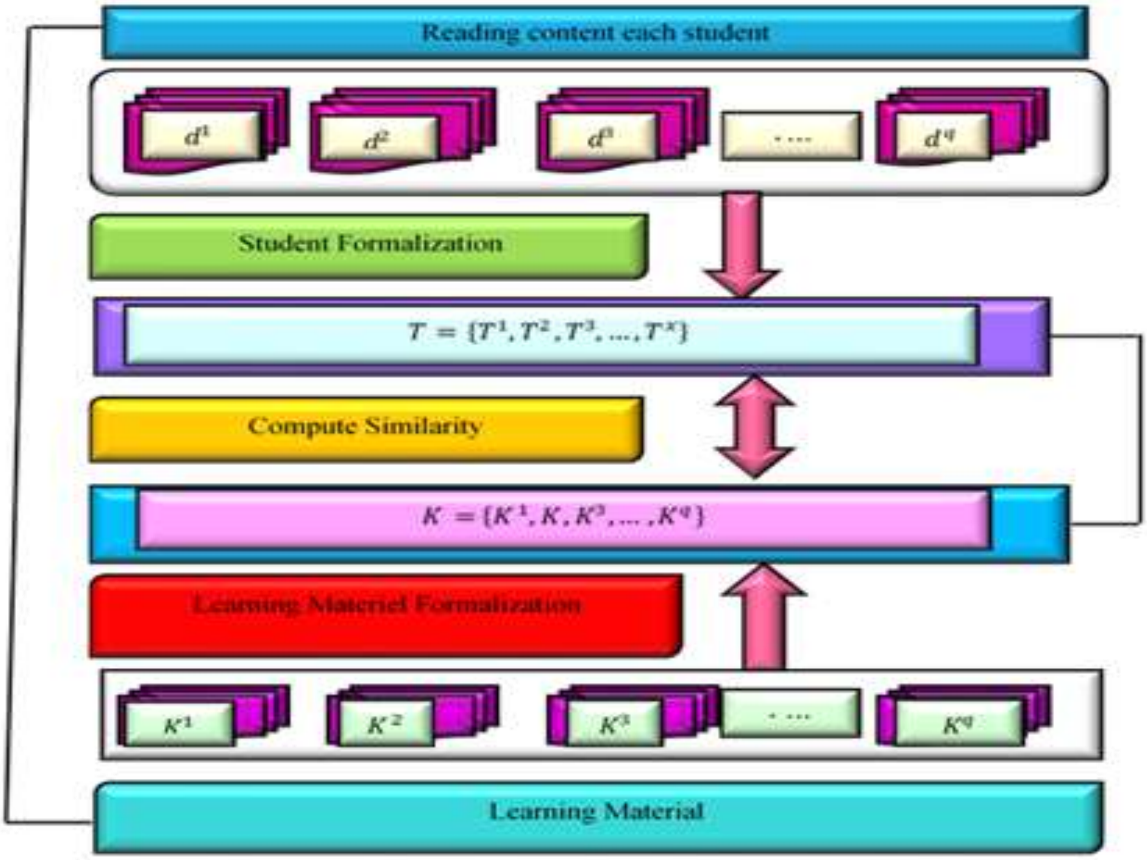
Figure 2. *The Proposed Architecture Diagram for IDSVR*

Student_I	Student_A	Sex	High_Schc	Scholarshi	Additiona	Sports_ac	Transport	Weekly_S	Attendan	Reading	Notes	Listening_	Project_w	Grade
STUDENT1	19-22	Male	Other	50%	Yes	No	Private	0	Always	Yes	Yes	No	No	AA
STUDENT2	19-22	Male	Other	50%	Yes	No	Private	0	Always	Yes	No	Yes	Yes	AA
STUDENT3	19-22	Male	State	50%	No	No	Private	2	Never	No	No	No	Yes	AA
STUDENT4	18	Female	Private	50%	Yes	No	Bus	2	Always	No	Yes	No	No	AA
STUDENT5	19-22	Male	Private	50%	No	No	Bus	12	Always	Yes	No	Yes	Yes	AA
STUDENT6	19-22	Male	State	50%	No	No	Private	2	Always	Yes	No	Yes	Yes	BA
STUDENT7	18	Male	State	75%	No	No	Private	0	Always	No	Yes	Yes	Yes	CC
STUDENT8	18	Female	State	50%	Yes	Yes	Bus	2	Sometime	No	Yes	Yes	Yes	BA
STUDENT9	19-22	Female	Other	50%	No	Yes	Bus	0	Always	No	No	No	Yes	CC
STUDENT1	19-22	Female	State	50%	No	No	Bus	12	Never	No	Yes	No	No	Fail
STUDENT1	18	Female	Private	50%	No	No	Private	12	Sometime	No	No	No	Yes	BA
STUDENT1	18	Female	Private	75%	Yes	Yes	Private	8	Sometime	No	Yes	No	Yes	Fail
STUDENT1	18	Female	Private	75%	No	No	Private	0	Always	Yes	No	No	No	Fail
STUDENT1	19-22	Female	State	100%	No	No	Private	0	Always	Yes	No	No	Yes	AA
STUDENT1	23-27	Male	State	75%	Yes	Yes	Private	12	Never	No	No	Yes	Yes	BA
STUDENT1	19-22	Male	State	50%	No	No	Private	0	Always	No	Yes	No	Yes	BA
STUDENT1	18	Female	State	100%	No	Yes	Private	0	Always	Yes	No	No	No	AA
STUDENT1	19-22	Male	State	50%	No	No	Private	0	Always	Yes	No	No	Yes	BA
STUDENT1	18	Female	State	75%	No	No	Private	12	Always	Yes	No	No	No	BA
STUDENT2	18	Male	Private	50%	No	No	Bus	2	Sometime	No	No	Yes	No	BB
STUDENT2	18	Male	State	100%	Yes	No	Bus	0	Never	No	No	Yes	No	AA
STUDENT2	18	Male	State	100%	No	No	Bus	0	Never	No	No	No	No	AA

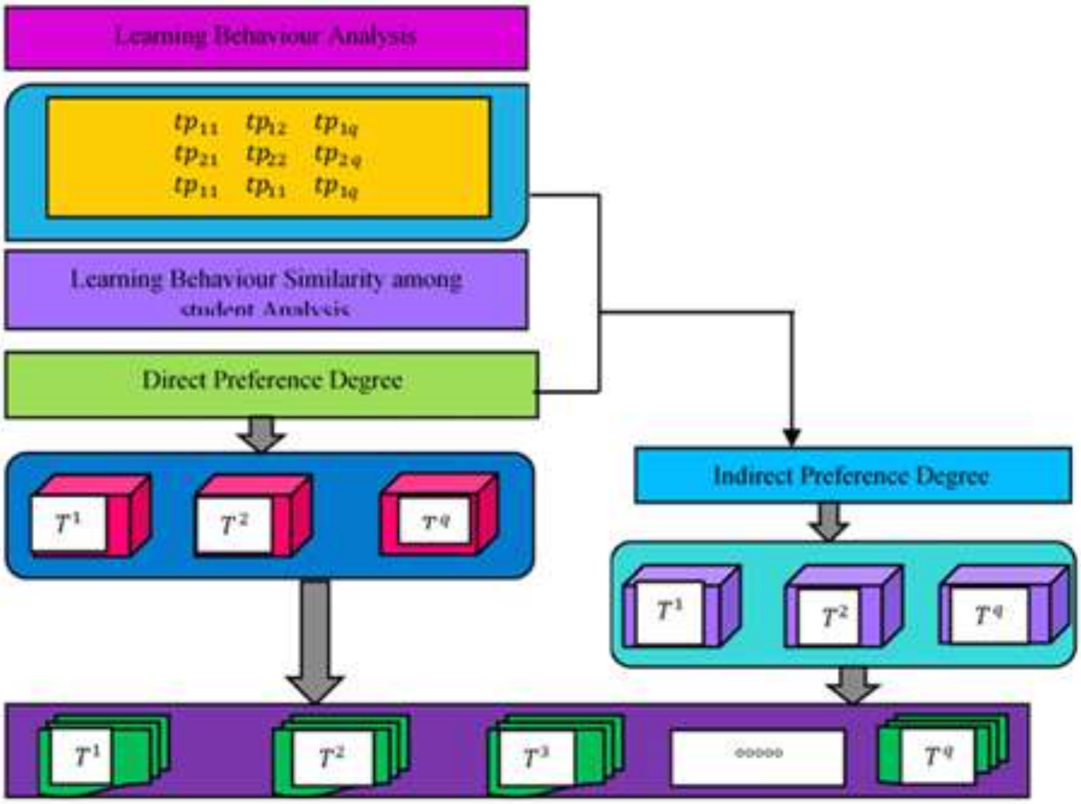
***Figure 3**. Student Performance Prediction Dataset*

***Table 2.** Student Performance Prediction Attribute Dataset Description*

S.No	Attribute	Definition
1	Student Id	Enabling personal observation and analysis.
2	Student Age	Student's age at the time of data collection
3	Gender	Analysis can be done by classifying male or female on the basis of gender of educational attainment
4	High School Graduate Category	Type of high school the student graduated from, such as public, private, or vocational.
5	Scholarship Type	Evaluating the impact of financial support on academic performance.
6	Additional Task	Indicates whether the student is engaged in extra- or part-time work outside of the course
7	Sports Activity	Indicates if the student participates in sports activities
8	Transportation	Represent the modes of transportation utilized by students to get from school.
9	Study Hour's	Explains study patterns and possible commitment to education.
10	Attendance	Reflect on student's attendance registers.
11	Reading	Grades in reading-related courses and assessments
12	Notes	Assessments and grading in subjects that involve taking notes.
13	Listening in Class	Lessons related to classroom listening and assessment scores.
14	Project Work	Signifies whether students are participating in project assignments or tasks
15	Grade	Evaluation criteria for each student's final grade or academic achievement



a)Direct Acquisition



b) Indirect Acquisition

Figure 4. *Preferred Learning Material Acquisition Process*

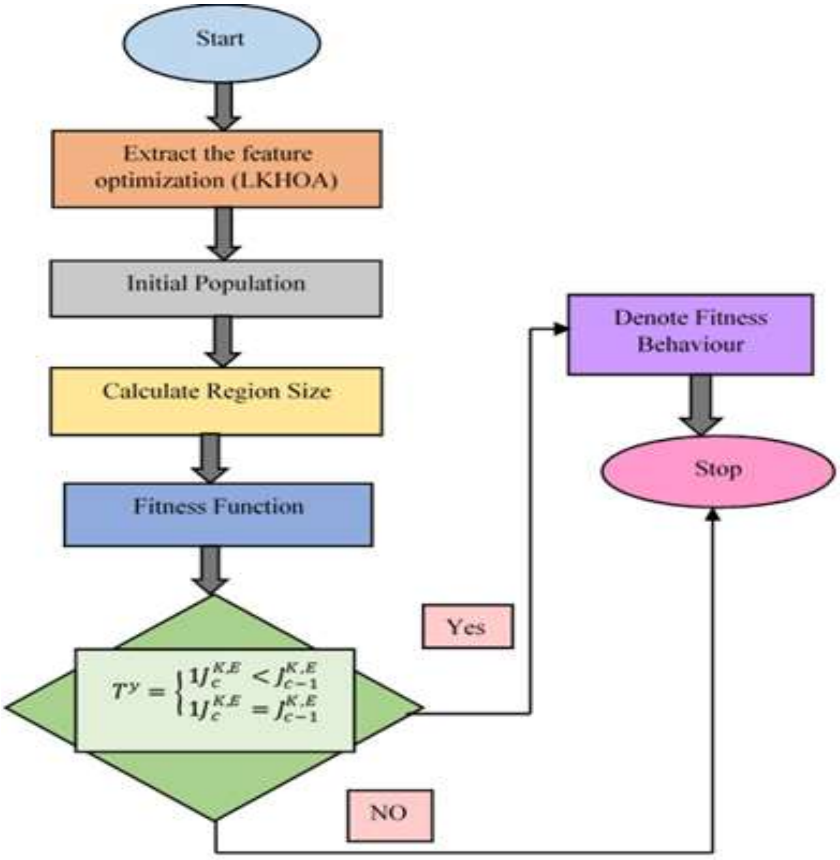


Figure 5. *The Diagram for LKHOA*

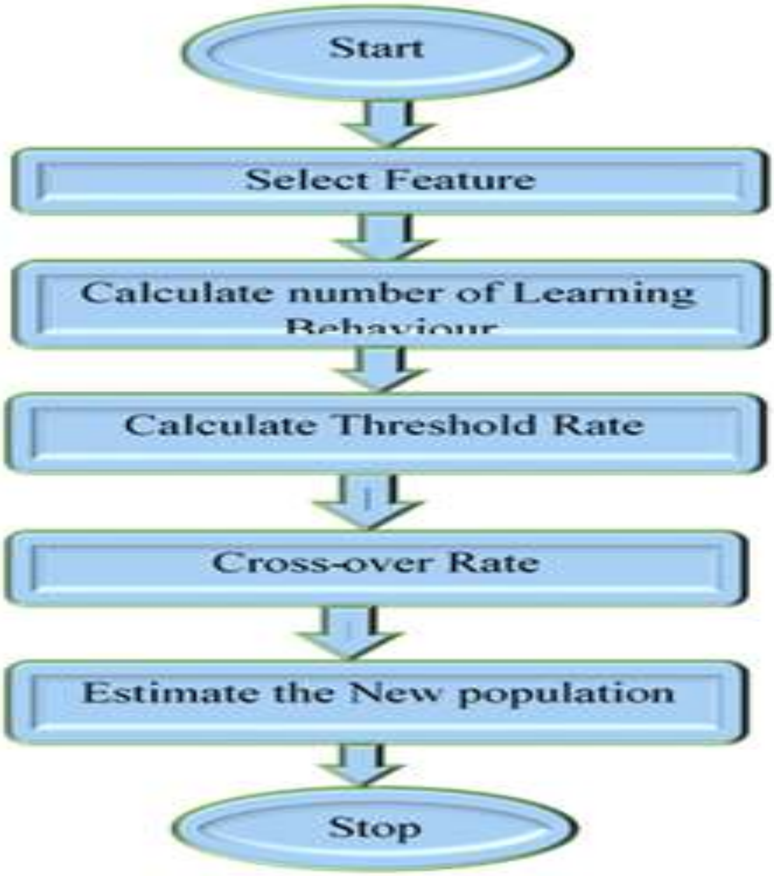


Figure 6. *The Architecture Design for FFLB*

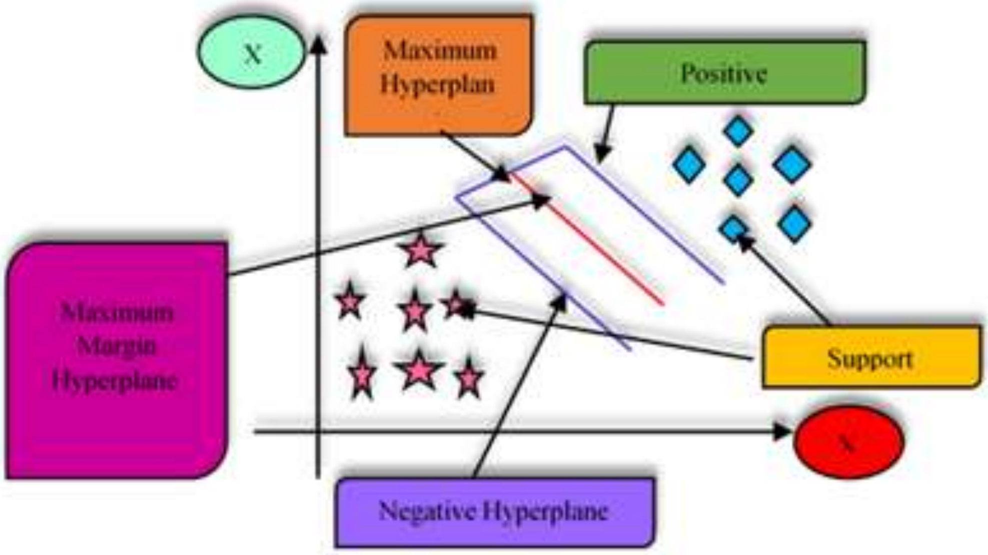


Figure 7. *The Structure Illustration for IDSVR*

Table 3*. Simulation Parameter*

Simulation	Value
Dataset name	Student Performance Prediction dataset
No of Records	149
Training	107
Testing	42
Tool	Jupyter
Language	Python

Based on the simulation parameters presented in Table 3, it is possible to predict the performance of keenly interested students. This also helps identify and ensure the quality of the training program. Furthermore, tools like Python language and Jupyter Notebook can be used to predict the performance of students of interest accurately.

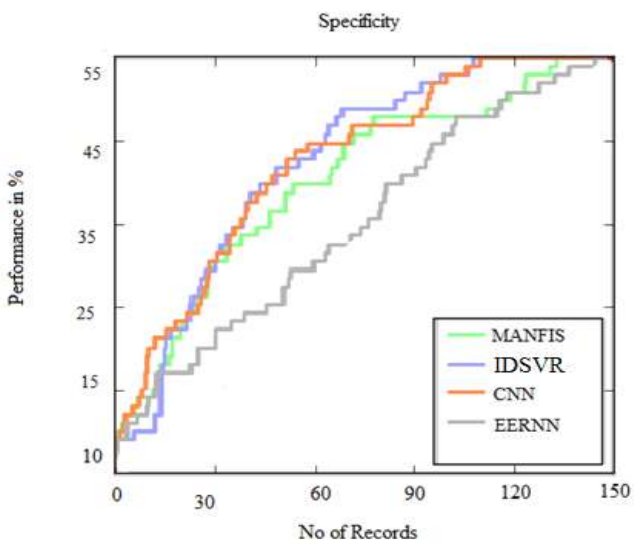


Figure 8. *Analysis for Specificity*

Based on the analysis of the student's specificity, as shown in Figure 8, the performance can be determined. Additionally, the proposed IDSVR method is used to evaluate the quality of training programs and identify the ones suitable for interested students through characteristic analysis. This IDSVR test method is especially valuable for evaluating student performance characteristics through measures that gauge the classifier's quality. According to the estimation of specificity analysis such as CNN, EERNN, and MANFIS obtained from literature, the value is as low as 46%. However, the proposed IDSVR testing and training method has improved the performance accuracy of students to 55%.

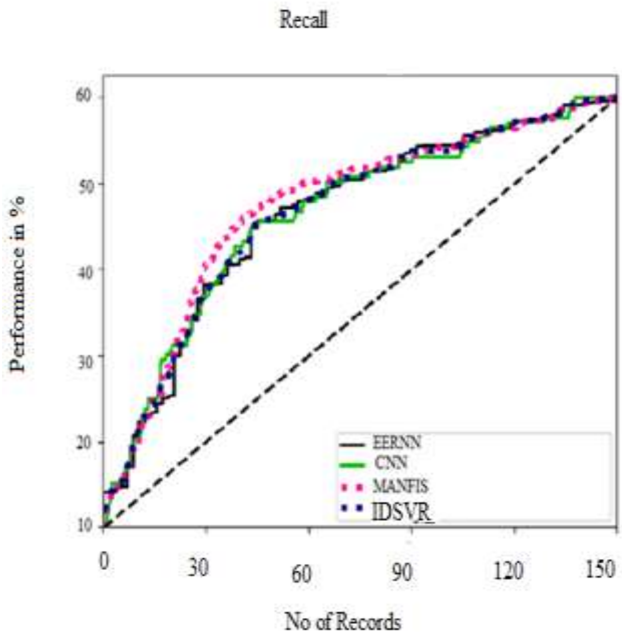


Figure 9. *Analysis for Recall*

As shown in Figure 9, the grades can be determined based on the student recall analysis. Also, the proposed IDSVR method can be used to evaluate the quality of training programs and to identify suitable programs for interested students through feature analysis. The percentages vary for the proposed algorithm in test mode and training mode. However, better performance should be achieved for other methods under the same conditions, and the results obtained should be compared with the student performance dataset. This testing method is valuable for analyzing the performance characteristics of students using measures to assess the quality of classifiers. A Recall analysis of EERNN, MANFIS, and CNN in the literature estimates the value to be 54% lower. However, the proposed IDSVR test and training method improves the accuracy of student performance by 62%.

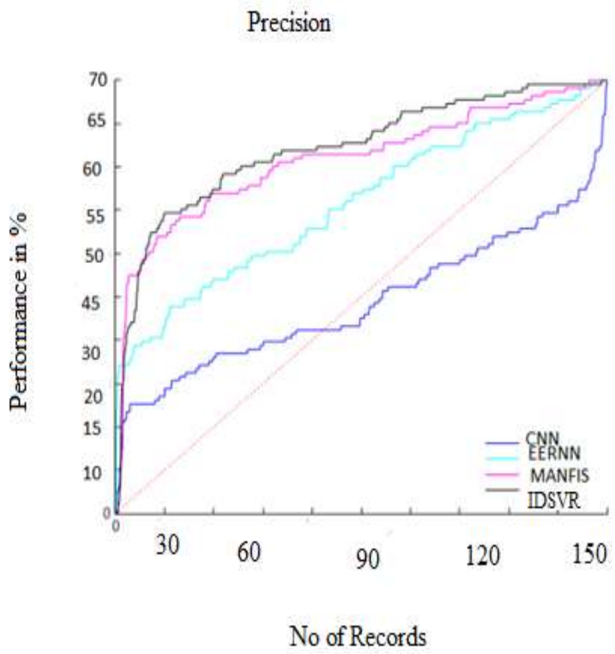


Figure 10. *Analysis for Precision*

Figure 10 shows that grades can be determined based on the analysis of student precision. The proposed IDSVR method can also be used to evaluate the quality of training programs and to find suitable programs for interested students through feature analysis. The percentages of the proposed IDSVR algorithms differ between the test and the training method. However, under the same conditions, other methods should achieve better performance, and the results obtained should be compared to student achievement datasets. This test method is valuable for analyzing student performance characteristics using measures to assess classifier quality. Accuracy analysis of MANFIS, CNN, and EERNN in the literature estimates this value to be less than 61%. However, the proposed IDSVR testing and training method improves the accuracy of the student's performance by 69%.

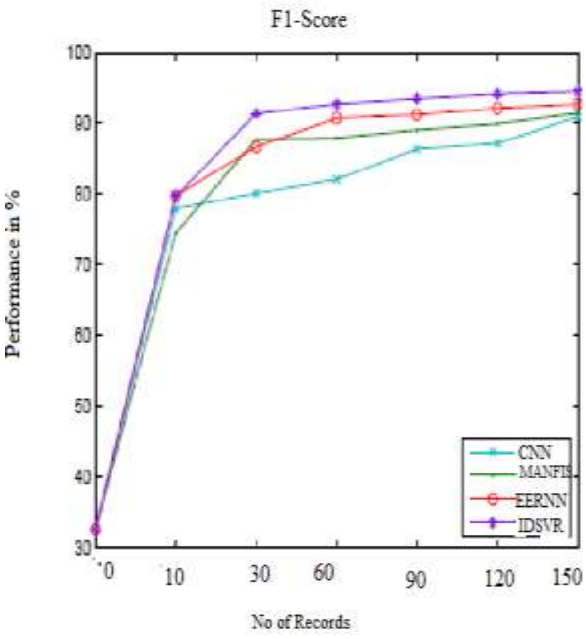


Figure 11. *Analysis for F1-Score*

Figure 11 demonstrates that the ratios can be determined based on the analysis of the student's F1 scores. The proposed IDSVR method can be used to evaluate the quality of tutoring programs and to identify suitable programs for interested students through feature analysis. However, other methods may achieve better performance, and the results obtained should be compared to student achievement datasets. The percentiles of the proposed IDSVR algorithm vary between the testing and training methods. This experimental method is valuable for analyzing student performance characteristics using metrics that assess the quality of the classifier. Nevertheless, the proposed IDSVR test and training method increases the accuracy of the student's performance by 89%. The F1-score analysis of MANFIS, CNN and EERNN in the literature estimates this value to be less than 71%. According to Figure 12, the ratio can be calculated by analyzing pupil accuracy. The IDSVR method can evaluate training program quality and determine appropriate programs for students through feature analysis. The accuracy percentages of the IDSVR algorithm vary based on testing and training methods, but using the proposed IDSVR method led to a 92% improvement in student performance accuracy. Previous analyses of MANFIS, CNN, and EERNN in the literature suggest accuracy values of less than 83%.

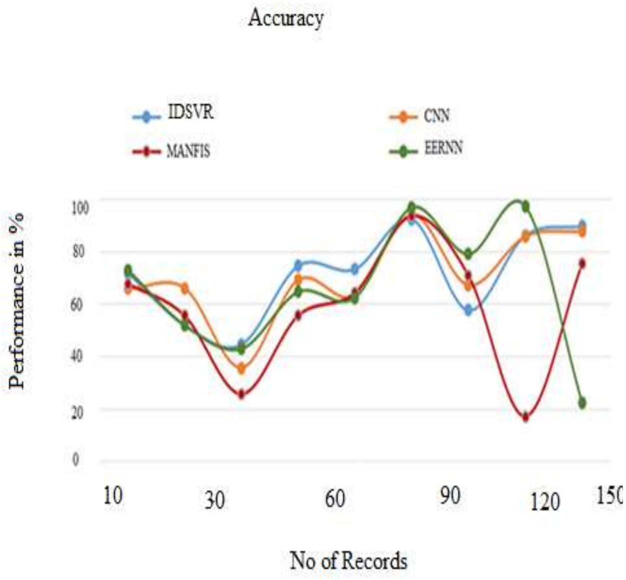


***Figure 12.** Analysis for Accuracy*

5. Conclusion

The IDSVR method has been proposed to identify and predict higher education students, compare their levels and grades, and achieve accuracy. Additionally, the learning performance prediction models are used as a useful method to ensure the quality of student learning materials. Furthermore, performance analysis presented among students is to develop diverse and accurate predictive models of academic implementation. The performance of ML algorithms in analytical techniques can be assessed using precision, accuracy, recall, f1 score and specific predictions. Another objective is to develop a framework to predict and evaluate student performance. A student performance prediction dataset from Kaggle can be used to identify student interest that predict student interest. Moreover, the PLMA technique is also used to assess the consistency of student learning behaviors. This method systematizes teaching materials and students, calculating the degree of similarity between the two. The LKHOA method enables the development of highly efficient feature extraction methods, converting raw data into processable digital features while preserving the information in the original dataset. Additionally, the FFLB technique is used to select features and evaluate their importance to students' learning behaviour, resulting in a more effective feature set. Finally, the IDSVR classification system, based on machine learning, can identify and assess quality assurance performance levels in training program activities. The IDSVR method proposed can estimate the training level and identify suitable programs for interested students through feature analysis. The percentages of IDSVR algorithms vary depending on testing and training methods. However, the proposed IDSVR test and training method increases student performance accuracy by 92%. This enables us to comprehend student performance from various perspectives, guarantee the effectiveness of learning methods in educational management, and ensure the quality of student performance predictions. Therefore, similar methods based on the described approach can be utilized to predict student performance. Machine learning is important tool and thus applied in different fields as reported in the literature [36-41].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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