The Scientific Temper (2024) Vol. 15 (spl): 404-413
E-ISSN: 2231-6396, ISSN: 0976-8653
Doi: 10.58414/SCIENTIFICTEMPER.2024.15.spl.47
https://scientifictemper.com/

RESEARCH ARTICLE

Quantitative transfer learning- based students sports interest prediction using deep spectral multi-perceptron neural network

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Abstract

Sports performance predictions are essential in understanding student interest rates. Early indications of student progress facilitate athletic departments to improve their learning interests and make students perform better. Interests in sports involve understanding key physical factors that significantly impact students' sports behavior and various other influencing factors. Deep learning techniques were used to develop a predictive model for student interest performance and support to identify the essential relationship influencing students' sports behavior. Identifying sports interests is complex because student interests represent different features. Existing methods cannot predict the features and the relationship between their related attributes. Therefore, previous methods had low accuracy high time, and error rate performance. To resolve this problem, a deep learning (DL) based sports interest prediction model was proposed using a deep spectral multi-perceptron neural network (DSMPNN) to identify student sports interests. Initially, the preprocessing is carried out by Z-score normalization to verify the actual margins of student interest rate to make normalization by comparing the ideal and essential margins of student interest through behavioral feature analysis using student behavioral sports interest rate (SBSIR). According to the feature dimensionality reduction, the non-relational features are reduced using the spider foraging feature selection model (SFFM) to select the essential features. Then, a deep spectral multilayer perceptron neural network (DSMPNN) is applied to predict student interest by class sports interest. The classifier proves the prediction accuracy, precision, and recall rate of up to 96% high performance to analyze the interests of the sport. The suggested system also produces higher performance than the other system.

Keywords: *Students, Sports behavior, Deep learning, Multi-perceptron neural network, Mutual, Behavioral feature analysis*.

Introduction

Sports performance prediction contributes to all educational institutions, and athletic to find sports training centers in creating training programs. To predict sports performance accurately, identify common elements and traits of social training and raise the standard for sports activity and training. At the same time, studying sports performance prediction models is important in improving practice and sports performance. Sports performance analysis and prediction play a critical role in the sports industry's development of equitable sports programs. Accurate prediction of athletic performance and discovery of performance patterns directly impact training and preparation goals. However, the current forecasts are based on a small amount of data, and there is significant uncertainty in the data generation process, Luo, M., Yu, Y., Xu, W., Zhang, Q., & Xia, J. (2020).

Establish a prediction model process for sports performance, analyze the factors affecting sports performance through experiments, and combine it with deep learning gradient compression model algorithm to improve sports performance. Deep learning (DL) is frequently used to map unknown input-output functions and linear correlations. It has been extensively employed in many fields due to its reliable performance, adaptability, signal transmission, and error re-propagation.

Initially, collect the dataset for students sports behavior analysis (like Hockey, cricket, etc.), and the first stage is preprocessing, used to normalize the dataset values and reduce the null values, evaluate the interest rate of the

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How to cite this article: Ahamed, A.B., Surputheen, M.M., Rajakumar, M. (2024). Quantitative transfer learning- based students sports interest prediction using deep spectral multi-perceptron neural network. The Scientific Temper, **15**(spl):404-413.

Doi: 10.58414/SCIENTIFICTEMPER.2024.15.spl.47

Source of support: Nil

Conflict of interest: None.

Received: 20/09/2024 **Accepted:** 30/09/2024 **Published**: 16/10/2024

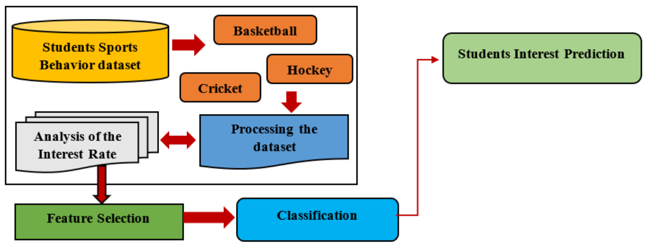

Figure 1: Basic Flow for Students Interest Prediction

student sports behavior using preprocessing feature marginal values. Selecting the relational features based on the interest rate, the classification stage is finally used to predict the students sports interest rate prediction, as shown in Figure 1.

Deep Spectral Multilayer Perceptron (DSMPNN) Neural Networks utilize their ability to capture complex patterns and relationships in complex data sets, making them powerful tools for predicting motor behavior. In this predictive framework, neural networks are trained on various sports-related data, including player statistics, and team performance metrics. The preprocessing step requires handling of missing values, and feature standardization to ensure model robustness.

DSMPNN combines structural layers, neurons, and activation functions for a specific prediction task. The network learns how to detect patterns and correlations through sample pooling and training and optimize the parameters through an iterative process. Evaluation on a separate set of test data verifies the model's generalization performance and provides insight into its performance through metrics such as accuracy.

Literature Review

The previous survey for primary school students' physical performance is impacted by various characteristics, including their physical makeup, level of physical exercise, and strengths. Sports performance forecasting and analysis can aid in improving equitable sports education and the objective selection of talent for the sports business. Treatments to increase engineering student success can be developed with an understanding of engineering students' performance patterns and potential impacts, Maphosa, M., Doorsamy, W., & Paul, B. S. (2023).

There are still many obstacles to developing reliable and effective analytic techniques. The significance of analyzing the critical elements influencing student success has been ignored despite numerous studies trying to create intelligent classifiers to predict student achievement. Administrators need to know this information to assess the academic program's strengths and shortcomings and implement corrective measures to enhance student results. A peer learning strategy known as Student-Led Teaching (SLT) improves student performance in electromagnetics (EM) courses, Alshanqiti, M., & Namoun, A. (2020), Serra, R., Martinez, C., Vertegaal, C. J. C., Sundaramoorthy, P., & Bentum, M. J. (2023).

Student's learning performance is one of the fundamental elements of evaluating the education system. Learning process Student performance in problem-solving is very important and one of the main factors in measuring learning achievement. However, personal characteristics are essential for improving students' academic performance because they allow us to understand the individual learning performance of each student. Extract HSEE (Higher School Entrance Examination) test takers' abilities based on individual test data and knowledge of education experts, and measure students' growth from junior high school to high school through aggregate marks and subject marks, Alhazmi, E., & Sheneamer, A. (2023), Chen, Z., Cen, G., Wei, Y., & Li, Z. (2023), Yao, Y., Zhang, Z., Cui, H., Ren, T., & Xiao, J. (2019).

Although monitoring each student's learning progress is a challenge for teachers using traditional teaching methods, individualized instruction in big classes is a terrific approach to increase the quality of instruction. Engineering students' academic achievement was contrasted with those who solely took general leave or did not take military leave. Only male students on military leave, analyses of gender differences were also conducted. Based on this study this paper focus to find students interest, Xu, Z., Yuan, H., & Liu, Q. (2021), Shariat, R., Seol, S., & Lenskiy, A. (2023).

It is not desirable to utilize prior academic performance to predict student performance because gathering many significant factors outside of past academic performance is challenging. As a result, it is imperative to make data collecting less challenging while still preserving timeliness and estimate accuracy, Sun, D., et al. (2023).

Providing users with clear and precise forecasts in this domain is challenging but also crucial. Recognizing pupils who are at risk since assessments vary depending on the situation. To elucidate the connection between teachers' work performance and students' performance, evaluate beginners. To address this problem is to understand the causes of student academic failure. However, most methods use practice-related aspects such as correctness and feedback, ignoring aspects of other student's behavior. A few studies have focused on student behavioral characteristics through subjective manual testing, and it is believed that different student behavioral characteristics can be equally used to predict student performance. However, the predictive accuracy is not sufficient, and the interpretation of predictions cannot be certain filtering. Students usually study additional materials that interest them, Butt, N. A., Mahmood, Z., Shakeel, K., Alfarhood, S., Safran, M., & Ashraf, I. (2023), Marbouti, F., Ulas, J., & Wang, C.-H. (2021), Liu, D., Zhang, Y., Zhang, J., Li, Q., Zhang, C., &

Yin, Y. (2020), Jiang, P., & Wang, X. (2020).

Data analytics (DA) is being considered increasingly in formal learning and online education due to the rapid advancement of educational technology. It offers broad direction and targeted resources to assist teachers in modifying for learners of different skill levels. These instruments generally focus on a particular handicap instead of a spectrum of abilities and offer minimal empirical support for their validity. Although current research indicates that this approach can be improved by classifying emotions and stress at multiple scales, sentiment analysis has been utilized to construct student behavior models for understanding emotions, So, J. C.-H., et al. (2023), Batanero, C., de-Marcos, L., Holvikivi, J., Hilera, J. R., & Otón, S. (2019), Tao, X., et al. (2022).

Predictions that are clear and precise are equally crucial. In this context, interpretability relates to how simple it is to hold the forecast, while accuracy refers to the anticipated value. Use a general formula to predict subjects' performance using A Multi-Source Spatial Attention Convolutional Neural Network (MSACNN). MSACNN creates structured features on student performance records by utilizing multi-scale convolution kernels. An end-to-end supervised deep learning model is created by feeding the SoftMax classifier with all the processed features, Alamri, R., & Alharbi, B. (2021), Zhang, Y., An, R., Liu, S., Cui, J., & Shang, X. (2023), Wang, P., Liu, J., & Liao, B. (2022).

Proposed Method

Student sports performance based on deep learning is decreasing the complexity of predictions. Deep Spectral

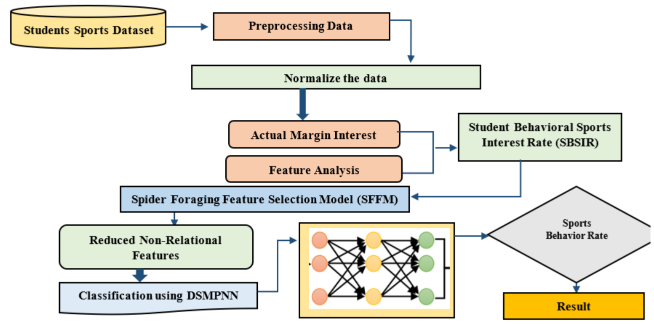

Figure 2: Proposed Flow diagram for DSMPNN

Multilayer Perceptron (DSMLP) analyzes numerous input features to predict student behavioral preferences accurately. Student sports performance data, train a model using a neural network, select weights and thresholds for the neural network through a Spider-Foraging Feature Selection Model (SFFM), and select important features for students' optimal creation of a sports. Deep Learning-Based Algorithm for Predicting Sports Performance of Students.

Figure 2 describes the proposed flow diagram for the DSMPNN algorithm based on these steps to predict student sports interest rate results. Initially, the dataset is extracted from the standard repository, and then the data values are in the preprocessing stage. Second step, these values evaluate the marginal values for student behavioral rate for student interest and maximum weighted interest rate using the analysis of the feature based on the Spider Searching Feature Selection Model (SFFM). It reduces the non-relational feature based on the threshold weights.

Table 1: Sample Dataset Set Description

Name	*Sport*	*Gender*	*Sports_ac*	*Weekly_S*	*Attendant*	*Individual*	*match_up*	*match_av*	*visit*	*play*	*tagged*	*interest*
Aaron Roc	Football	Male	No	0	Always	999	null	null	1	1	1	Football
Adam Sco	Golf	Male	No	0	Always	999	null	null	1	1	1	Cricket
Adrian Go	Baseball	Male	No	0	Always	999	null	null	1	1	1	Rugby
Alex Rodr	Baseball	Male	No	2	Always	01-06-2021	null	null	0	0	1	Football
Alfonso So	Basketball	Male	No	12	Always	999	null	null	0	0	1	Cricket
Amar'e St	Basketball	Male	No	2	Always	01-06-2021	null	null	1	1	1	Rugby
Barry Zito	Baseball	Male	No	0	Always	999	null	null	1	1	1	Football
Blake Grif	Basketball	Male	Yes	2	Sometime	01-06-2021	null	null	1	1	0	Cricket
Branden A	Football	Male	Yes	0	Always	999	null	null	0	0	0	Rugby
Brandon N	Football	Male	No	12	Never	999	null	null	0	0	0	Football
Carl Crawf	Baseball	Male	No	12	Sometime	999	null	null	1	1	0	Cricket
Carlos Dur	Football	Male	No	8	Sometime	01-06-2021	null	null	1	1	0	Rugby
Carmelo A	Basketball	Male	No	0	Always	999	null	null	0	0	0	Football
CC Sabath	Baseball	Male	No	0	Always	01-06-2021	null	null	1	1	1	Cricket
Chris Paul	Basketball	Male	No	12	Always	999	null	null	0	0	1	Rugby
Chris Bos	Basketball	Male	No	2	Always	01-06-2021	null	null	1	1	1	Football
Cliff Lee	Baseball	Male	No	0	Always	01-06-2021	null	null	0	0	1	Cricket
Cole Hamm	Baseball	Male	No	2	Always	999	null	null	1	1	1	Rugby
Darrelle R	Football	Male	No	12	Always	01-06-2021	null	null	0	0	0	Football

Finally, the classification step in DSMPNN, which predicts the interest rate and categorizes the result class by class.

Dataset collection

Students Performance predictor datasets are a valuable resource for those interested in understanding and improving student's sports performance. Its feature set allows to build predictive models and explore factors contributing to student success. This complete data set facilitates predictive analytics regarding student's sports shown in Table 1.

Together, these attributes provide a complete view of each student's movement and profile, which can be used for various analyses, including predictive modeling, identifying influencing factors, and evaluating the different variables on student interest rate.

Data Preprocessing

Information about the essential characteristics of the students, their Interest in sports (stimulating, maintaining, and developing situational Interest), and Values will be identified and entered, or rows/columns will be deleted with missing data. Eliminate duplicate entries in data sets.

Z-score Normalized data

During a preprocessing step, normalization is breaking down the numerical characteristics of the data and putting the values inside a range.

$$Zscore = \frac{N-\mu}{\sigma} \quad (1)$$

Normalization changes the data values in a dataset to a common scale without changing differences in the range of values. Usually, new boundaries are defined (0, 1), (-1, 1)), and the data is transformed accordingly. If a value is exactly equal to the average of all values for that feature, it is normalized to 0.

$$\mu = \frac{1}{n}\sum_{x=1}^{S}\left(S_x\right) \quad (2)$$

$$\sigma = \sqrt{1/n\sum_{x=1}^{S}(S_x-\mu)^2} \quad (3)$$

The process of rescaling the original data without changing it is a technique often applied as part of data preprocessing.

$$Z = \sqrt{\frac{\sum(s-\bar{s})^2}{n}} \quad (4)$$

This allows the data to identify the probability that the score will occur within the normal distribution of the data.

Normalization modifies the data in the data set's value range; it does not alter the value range itself.

$$s_{scalling} = \frac{S-S_{max}}{S_{max}-S_{min}}$$

$$S' = \frac{s-\mu}{\max(s)-\min(s)} \quad (5)$$

Min-max normalization relations between original data values and performs a linear transformation.

$$S' = x + \frac{\left(s-\text{minimum}(s)\right)(x-y)}{\max(x)-\text{minimum}(x)} \quad (6)$$

$$S_{normalize}^{(x)} = \frac{x^s - S_{min}}{S_{max}-S_{min}} \quad (7)$$

$$S = \sqrt{\frac{1}{(s-1)}\sum_{x=1}^{x}(S_x-y)^2} \quad (8)$$

Finally, the score for each metric is linearly scaled between 1 and 100 using min-max normalization. The final total score is scaled again using min-max normalization. 100 represents the highest total score, and 1 represents the lowest total score. The standard deviation of the row is equal to 0, and all values in the row are set to 0. The min-max standardized Z-score also shows a range of values from 0 to 1.

Student Behavioral Sports Interest Rate (SBSIR)

Appropriate value options must be evaluated based on the interest's valuation to analyze the essential margin of student interest through behavioral characteristics using the Students Behavioral Sports Interest Rate (SBSIR).

$$S_B = \sum_{x=1}^{n}\sum_{v \in n_x} |v-\mu_x|^2 \quad (9)$$

Where S_B - Student behavior, v -represents dataset, n -number of the dataset, *interest* rate of the number of samples,

$SP_x = \sum_{v \in n_x}\frac{1}{N(n_x)}|v-\mu_x$, Initially, set ($v$) and the threshold SP_x of the minimum number of samples in the dataset. Each dataset value is then associated with a threshold, and each dataset evaluates a feature's value.

$$\Delta SP_x = SP_x - v$$

$$\Delta v_x = v_x - v$$

Then, calculate the error ΔSP_x of the SP_x evaluation index and the difference between the number of samples in the cluster and the initial value.

$$\Delta N_x = \frac{Int\left(\Delta SP_x\right)-1}{2} + \frac{Int\left(\Delta SP_x\right)+1}{2} * \Pi(\log_n(\Delta SP_x+1))\theta\left(\Delta SP_x\right) \quad (10)$$

If $v_x > v$, then Δv_x is negative, $Int\left(\Delta SP_x\right)-1$ represents that when the number of data interest in the $Int\left(\Delta SP_x\right)+1$

Less than the initial value and the minimum value of the index and it reduce features dimensionality of sports interest.

Margin Level of Student Physical Education Data Input Component (G), G^D is the vector representing each value's student sports interest score. And G_x - column of the value of each sport.

$(x, y) \in \Omega$ Uses the G^D and G_x to calculate the interest rate,the sports performance rate's hidden characteristics in the performance matrix.

$$Sx = Tanh\left(G^D * I_w\right), Sr = Tanh\left(G_x * I_w\right) \quad (11)$$

$Sx, G_x \in G^D$ Is the potential factor of the student margin weights, $SIR \in G^{m*x}, WI \in G^{m*n}$ is the characteristic vector of the sports substances. An activation function is used to obtain a result in different weight feature vectors. Each student's performance as well as the attributes of each sport have different levels of significance and can be expressed using the following formula:

$$XSR = softmax\left(sx * w_{xs}\right) * sx, XSR = softmax\left(sx * w_{xs}\right) * sx \quad (12)$$

It transforms multiple cognitive layers, simulates the special structure of the data, and performs an interest of students' hidden behavior and hidden units $Ns = sigmoid\left(XSR * WM^{'} + Si\right)$ to obtain predicted performance values. The main objectives are to compute the interest ratio of feature weights, decrease computation as dimensionality is reduced, and enhance the descriptive power of the model.

Feature samples were drawn from the target population in three broader sports interest rate categories such as interest <90, interest <80, interest <70, interest <60). Figure 3 shows the sports interest rate analysis.

Spider Foraging Feature Selection Model (SFFM)

Social spiders maximize their activity on webs vibrant. Sociable spiders construct their nests in groups. Signals

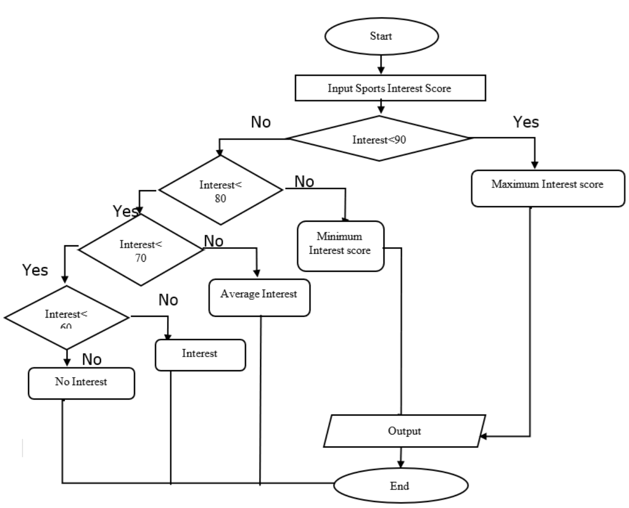

Figure 3: Flow chart for Sport Interest Rate

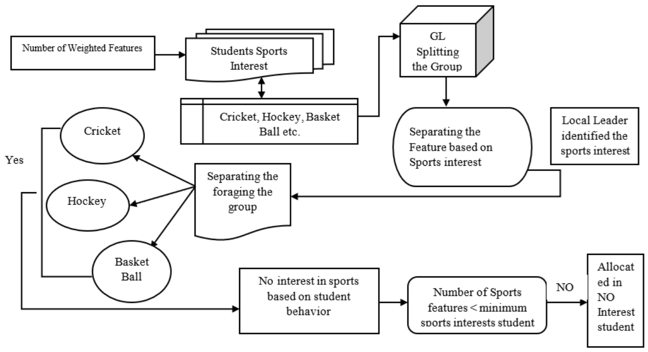

Figure 4: Spider Foraging Feature Selection Performance

are transmitted via the webs by these spiders to convey messages among themselves or to detect the presence of target vibrations, spiders are known to be highly attentive in their ability to differentiate between those of target spiders. Thus, social foraging in spiders aims to locate a target by option up vibrations along the web that the target produces.

Figure 4 depicts the, Spider's performance analysis weights the number of features based on students' sports interests (cricket, hockey, basketball, etc.) and, in a second step, weights the number of features based on the features used by global leaders for sports interests. If the leader does not find enough interested students, the group is divided into smaller groups, and the groups are split up to forage. Individual student features may not be aware of traits that are highly valued in the same place due to shared approval and their behavior during the interaction reflects that they are part of a larger group.

Social Spider Optimization (SSO) Weight Calculation

Each spider or Feature like ID, Sports activities,grade,age, and attendance is assigned to a weight based on the fitness value of the solution each neural. Cooperative weights are calculated in the Local and global level evolution of search sets. To a spider position of maximum minimum features weights are represented by the hidden network (sf) within the two search agents one is global another one is local.

$Global\left(G_s\right)$, $Local\left(L_s\right)$ and N_s Randomly select from 75 to 95% of the total student interest rate between sensitive and non-sensitive features (f), with the remaining G_s considered as global leader individuals ($G_s = sf - f_s$),

All spider has a weight (f_{wi}) according to their solution suitability, and that weight is calculated as follows:

$$Related_{fw} = \max_{n=\{1,2,3...F\}} sf(N) \quad .$$

$$Non_{Related_{fw}} = \min_{n=\{1,2,3...F\}} sf(N) \quad (13)$$

According to the correlated feature weights $\max_{n=\{1,2,3...F\}} sf(N)$ and $\min_{n=\{1,2,3...F\}} sf(N)$

$for(n=1; n<sf+1, n++)$

Calculate $Related_{fw}$ and $Non-Related_{fw}$

$if(f_{wi}<f_s)$, Where $f_{wi} \in random(0,1)$

$$sf_n^{n+1} = f^n + \propto {}^* G_s {}^* (f_{wi} - f_w^n) + \beta {}^* (f_{wi} - f_w^n) + \delta {}^* (random - 1/2)$$

$Elseif$

$$sf_n^{n+1} = f^n - \propto {}^* (f_{wi} - f_w^n) + G_s {}^* \beta {}^* (f_{wi} - f_w^n) + \delta {}^* (random - 1/2)$$

End if

End for

Here, $Related_{fw}$ is the fw the maximum weightage feature like (Age, sex, interest student, games, attendance, grade), $n \in 1, \dots N$ and Information exchange, such as minimum and maximum values, optimal feature values, average weights, etc.

SFFM

Spiders achieve this task by communicating finished vibrational indications that travel along the web threads. Spiders are search agents, and the Web is a search space for optimization problems.

The vibrations used to determine their weights and those made by other spiders are notable with a high degree of accuracy by the spiders.

$$f_{1,m} = \left(\frac{\left(Fw(x_{t,s}) - fw_{min} \right)}{\left(fw_{max} - fw_{min} \right)} \right) + Sf \qquad (14)$$

Where $Fw(x_{t,s})$-fitness values of evaluated objective function and the spider position $x_{t,s}$, the variables of fw_{max} and fw_{min} maximum and average fitness.

$$f_x(f,n) = \sum_{x=1}^{n} s_x^2, \qquad x^n = (0, \dots m); f(x) = 0 \qquad (15)$$

$$Related_{fw} = \max_{n=\{1,2,3\dots F\}} sf(N)$$

$$Non_{Related_{fw}} = \min_{n=\{1,2,3\dots F\}} sf(N) \qquad (16)$$

The identification of sports interests is complex, and the number of irrelevant features is reduced. The spider's movements are related to vibrations that nearby spiders sense. Additionally, spiders can move toward the nearest member to investigate the search space. $Vi_{x,y}$, with the maximum frequency f_{max}. Therefore, the entire spider population produces the highest vibrations among the spider populations, but below the prey vibrations v_{target} s:

$$Vi_{x,y} {}^* (x_m - x_f) {}^* \theta_1 \qquad (17)$$

The spider moves based on the vibrations it senses from its target. This is a result of the spiders closest to the target sensing the greatest vibrations from the target and, therefore, moving first towards the most adapted target throughout the web.

$$Vi_{f,x} {}^* (x_n - x_f) {}^* \theta_1$$

$$x_{n+1} = x_f + Vi_{f,x} {}^* (x_n - x_f) {}^* \theta_1 + Vi_{x,y} {}^* (x_m - x_f) {}^* \theta_1 \quad (18)$$

θ_1 - The target values of the spider are calculated and the random number $x\,rand(1-r)$ .Spider S x_m after receiving updates from the nearby spider vibration it's f_{max} if this vibration is higher but not equal to that of the nearest adjoining spider, by choosing its strongest vibration to f_{ave}. Else, it preserves its f_{max}. After that, the spider walks randomly toward the strongest vibration.

Figure 5 is a new individual, snew (new spider), created in the SFFM through mating between dominant male M_s and female individuals within a given range, r. Weightier elements are more likely to affect private fresh snow; the weight of each spider determines the probability of each spider's influence on new. When a new spider forms, its fitness is evaluated against the other spiders in the colony. If the new spider's fitness is higher than that of the worst spider, the worst spider is replaced by the new spider or features values.

Deep spectral Multi-Perceptron Neural Network (DSMPNN)

To increase the performance of DSMPNN in sports data classification, evaluate the improvement of the classification method by optimizing the neural network layer weights and parameters. Each neuron can perform a DSMPNN to calculate weighted feature values in each hidden neuron, as shown below.

$$S_x = \sum_{i=1}^{n} w_{xy} x_i + \beta_y \qquad (19)$$

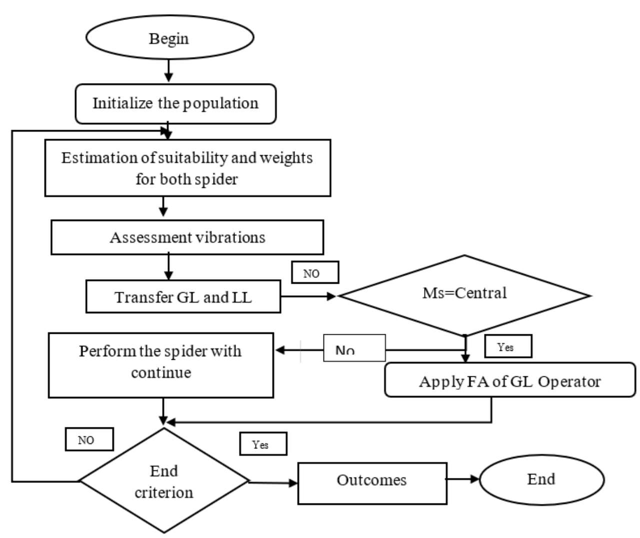

Figure 5: Flow chart for SFFM

Where w_{xy} -joining weight, β_y - biased time, x_i Indicates entry and displays the total number of entries. To determine the neuron's output, use the activation function. Use the results of hidden neurons to output the neuron's final output O_n

$$O_n = \sum_{x=1}^{n} w_{xy} x_i * \beta_y \quad (20)$$

Weights and biases affect MPNN performance, and training an MPNN involves determining the ideal weights and biases. A hidden layer that calculates the maximum and minimum feature values using time and the total number of selected features (gender, relevance_available_360, attendance, playing, tagged, game activity, sport, interest) is classified based on which sport the student is interested in and how much the student is interested**.**

MPNN Training

The representation of candidate solutions to train the MPNN and the representation of the fitness function used to assess the solutions of primary considerations in the creation. Each solution provides a set of settings for the MBNN weight and bias parameters.

$$w_l = \begin{bmatrix} w_{1,l} & \cdots & w_{n,l} \\ \vdots & \ddots & \vdots \\ w_{1,h} & \cdots & w_{n,h} \end{bmatrix}$$

$$\beta_l = \begin{pmatrix} \beta_l \\ \cdots \\ \beta_n \end{pmatrix}$$

$$w_1^{'} = \begin{bmatrix} w_{1,l} & \cdots & w_{n,l} \\ \vdots & \ddots & \vdots \\ w_{1,h} & \cdots & w_{n,x} \end{bmatrix}$$

$\beta_2 = \begin{pmatrix} \beta_l \\ \cdots \\ \beta_n \end{pmatrix}$ where $w_{1,l}$ - weights values of the connections between input (i) and hidden (h)neurons. The connections between the hidden neurons and their outputs have an inverted weight matrix. Regarding hidden and output neurons β_2 and β_l represent the bias values.

Neurons in Multilayer Perceptron Neural Networks are classified as hidden neurons if they have connections between their input and output. A neural network's input is limited to hidden and output neurons, and each neuron has an activation function. Let T be the input of the hidden layer's link weight, Mn On be the hidden layer's output, f be the connection weight between the hidden layer and the output layer, and m be the number of hidden neurons.

$$DSMPNN\ output = \frac{1}{N} \sum_{x=1}^{N} DSMPNN_{Mp} \ for\ N = 1,2,..,X\ ,$$

Let X - number of multi-neural layers,

$$DSMPNN_{np} = M\left(\sum_{M=1}^{n} \left(M_n O_n\right)\right) \quad (21)$$

The Hidden neural network of

$$DSMPNN : M_n = f\left(\sum_{x=1}^{m} \sum_{y=1}^{n} w_n T_{xy}\right) \quad (22)$$

Figure 6 shows that in a single-layer perceptron, the output O_n is calculated by multiplying the input x by the weight M, adding the bias b, and finally obtaining nonlinear values. As shown in the figure above, have an input layer, two hidden layers, and an output layer, where the superscript in M denotes the number of layers.

Sports Behavior Prediction Rate

Considering sports performance data values as a set of uneven time series, construct an appropriate level model for sport behavior prediction ratio,

$$\begin{pmatrix} I \\ P(I) \end{pmatrix} = \begin{Bmatrix} P_1, P_2, P_3, \dots P_n \\ R(P_1), R(P_2), R(P_3), \dots . R(P_n) \end{Bmatrix} \quad (23)$$

The information entropy of the distribution characteristics of the game interest level is as follows.

$$H(SR) = E\left(N\left(S_n\right)\right) = \sum_{x=1}^{n} N\left(S_x\right) log_2 N\left(S_n\right)$$

Test cumulate of time series *X* for sports behavior rate of a student,

$$S = \frac{\left(s_x - \bar{x}\right)\left(s_{x-n} - \bar{x}\right)\left(s_{x-N} - \bar{x}\right)}{\left(x_n - \bar{n}\right)^3} \quad (24)$$

The average value $N(x) = \frac{1}{n}\sum_{n=1}^{n} x(n)$ *x (n)* of Interest in sports behavior using multivariate variables, statistical

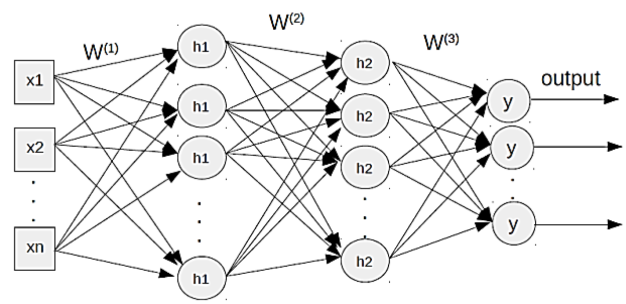

Figure 6: MPNN Architecture

features of sports expressed as scores and accuracy of sports performance prediction

$$S_1 p^{\lambda_i S} + S_2 p^{\lambda_2 S} \left(\lambda_1 \neq \lambda_2\right)$$

$$Si\left(xi_1, xi_2, n\right) - Ri\left(xi_1, xi_2, m\right) + \int \frac{\left(n\left(xi_1, xi_2, n\right) - \right.}{\left. Ri\left(xi_1, xi_2, m\right) SSBi < n(|\,xi - yj\,|^2 + n(|\,xi - yj\,|^2)\right)} \tag{25}$$

Expected output (O_n); $N = \left(n_1, n_2, \ldots, n_x\right)$ and connecting the weights of each neural network in input and hidden layer; $H = \left(h_1, h_2, \ldots, h_x\right)$ and the connection weights between the hidden and output layers.

$O_n = Mp\left(\sum_{x=0}^{n} w_{xy} H_y\right)$ Continue to optimize the connection weights w_{xy} axy and H_y until have high accuracy;

$$\triangle w_{xy} = -\eta * \frac{\varepsilon A}{\varepsilon w_{xy}} \tag{26}$$

$$\triangle H_y = -\eta * \frac{\varepsilon A}{\varepsilon H_y} \tag{27}$$

Determine the initial connection weights during athletic performance modeling. Therefore, use the DSMPNN algorithm to determine the most reasonable connection weights. The hidden layer obtains the prediction results with large deviations, and the return value-sending layer removes the errors until a high-precision prediction result is obtained.

MLPNN consists of a structure (input layer, hidden layer, output layer, and dependent term) with weights as tunable parameters of the model. The system is established can model Evaluating the weights based on predicted and output. As shown in Figure 7, the number of layers and units per layer determine the feature complexity.

Result and discussion

A Neural network is employed in this training class to evaluate the effectiveness of the suggested solution. Matrix analysis and result versions were used to test the result parameters. Compared to the approach used in previous experimental findings, this implementation yields more efficient results.: Particle Swarm Optimization-Support vector Machine (PSO-SVM)(Guo /2020); Long short-term memory model (LSTM) (B. Zhang/2020); Random Forest (RF) (Kai Liang/2022); and Neural Network (NN) (X. Zhang /2021) compared with proposed model Deep Spectral Multi-Perceptron Neural Network (DSMPNN) predicting the accuracy result better than previous approaches.

Table 2: Proposed Simulation Values and Parameters

Parameters used	*Values*
Dataset Name	Student Sports Activity dataset
Language	Python
No.of.Records	2000 records
Features Count	<20
Classified class	3(Minimum, Average, Maximum)

Table 2 shows the details of the simulations used to evaluate the performance produced by the different methods. Therefore, the performance of DSMPNN process was measured under various parameters. The confusion matrix assesses the following parameters:

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\left(\text{TP} + \text{FP} + \text{FN} + \text{TN}\right)} * 100 \tag{28}$$

This section explains in detail the results obtained. It contains the student's list of sports interests, which the model collected by testing the interest values.

As shown in Figure 8, the classification accuracy performance is determined by comparing different methods' average precision and recall, and student performance characteristics on their collective dataset, which contains 30% of records from the community.

An equation is used to determine the precision of the sport interest prediction.

$$\text{Accuracy}\left(\text{A}\right) = \frac{\text{Actual predict value} + \text{number of positive values}}{\left(\text{Total number of data}\right)} \tag{29}$$

Figure 9 shows the accuracy performance analysis of results from different methods. This method uses the SFFM technique to estimate the weights of motor behavior-related features and helps select the best features in the category hierarchy. As a result, the suggested method produces better

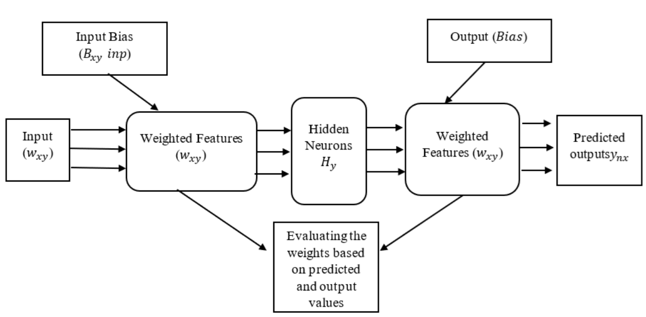

Figure 7: MPNN Process

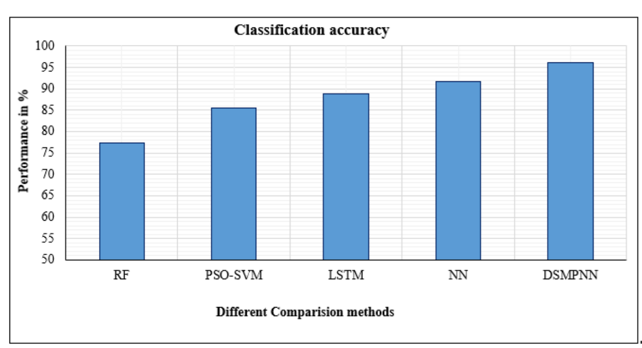

Figure 8: Performance of classification accuracy

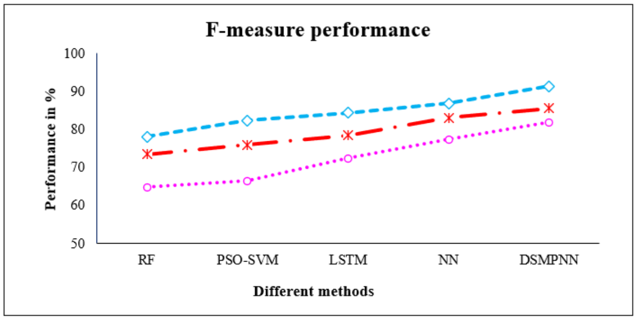

Figure 9: F-measure

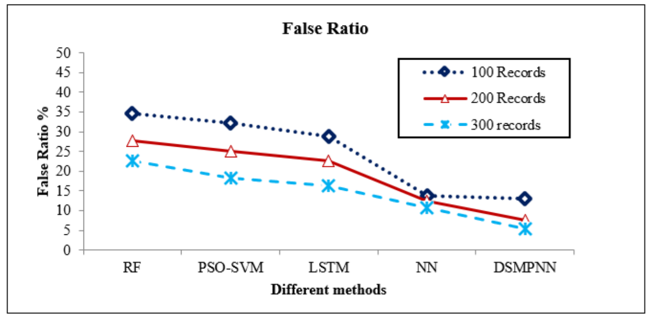

Figure 12: Analysis of False Classification Ratio

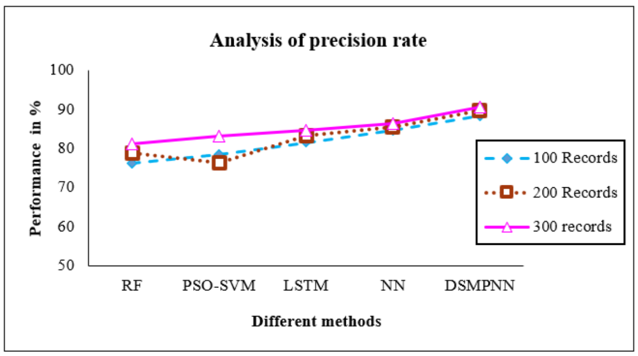

Figure 10: Analysis of precision rate

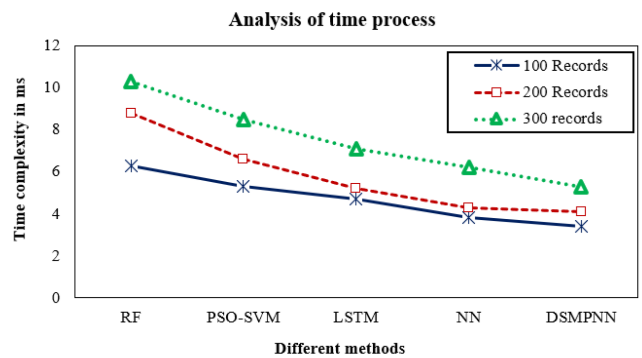

Figure 13: Analysis of the time process

F measurement findings compared to previous methods. The accuracy evaluation of precision estimation employing various approaches is presented in Figure 10. This method uses the DSMPNN method to produce feature patterns related behavior, which help detect critical levels. Therefore, the proposed method produces results with better precision than previous methods.

Figure 11 shows the playback performance as determined by multiple techniques. Furthermore, the suggested DSMPNN algorithm outperforms earlier techniques in terms of performance. The proposed evaluation takes advantage of the correlation properties of levels. Therefore, the proposed approach effectively improves the identification of interest levels in collective data sets.

Figure 12 defines the analysis of misclassification performance compared to previous methods. The proposed approach preprocesses the dataset to remove unnecessary records from the collective dataset. Next, DSMPNN is used to analyze the characteristics of ranked relationships. Then, the features are divided by class labels based on the marginal rate. Finally, to categorize and select features and the proposed misclassification performance results at 5.4%, which is lower than other methods.

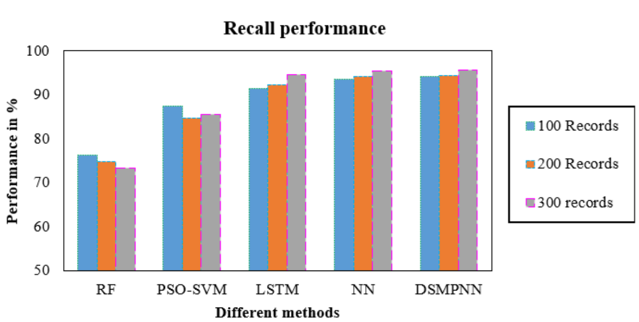

Figure 11: Analysis of recall rate

The time process of the execution process is depicted in Figure 13 above. The suggested DSMPNN algorithm has a faster generation time than other techniques. Milliseconds are used to calculate the time complexity. Whether an upper bound is a lower limit is represented asymptotically during instruction processing using the asymptotic notation O(n).

Conclusion

To conclude a sports students' behavior prediction performance regarding categorization accuracy, a feature selection step was developed and analyzed to effectively predict and apply the determined prediction. These data indicate a strong desire for sports behaviors in students, as well as a prediction of students' Interest in sports using the proposed DSMPNN model. Deep Learning (DL) data are treated as input, and data augmentation is performed during preprocessing. Subsequently, the proposed model's classification accuracy is enhanced by employing the DSMPNN model for the interest prediction process. The analysis considers two data ratios: 80%-20% and 60%-40%. The proposed model DSMPNN achieved 96.02% accuracy. This algorithm exhibits higher prediction and lower error rates of students' sports performance when compared to existing methods. The proposed method improves the accuracy and prediction of students' sports interest performance.

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