HFIPO-DPNN: A Framework for Predicting the Dropout of Physically Impaired Student from Education

Marina. B* and A. Senthilrajan

***Abstract*—Education plays a significant role in individuals' development and the economic growth of developing countries like India. Dropout of students from their studies is the major concern for any order of education. Some models for predicting the dropout of students are developed with several factors. Many of them lacked consistency as they backed their studies with the academic performance of the students. Especially, for those students who suffered from physical impairment, the dropout depends on several external factors. Hence, this work proposes a novel HFIPO-DPNN to predict the student dropout rooted in the previous semester's marks. The proposed model enclosed the hybrid firefly and improved particle swarm algorithm to optimize the feature selection that influences the dropout of hearing-impaired students. The optimized feature data are used to predict the dropout with the novel DPNN. The optimized data was split and used for training the DPNN. The testing data is used to evaluate the performance of the proposed framework. The attributes used for predicting the student dropout are Family Size, Subject, Medium of Instruction, and so on. The data must be collected from 250 physically impaired children belonging to ITI institute, Bangalore. The outcome of the proposed framework is evaluated on several metrics. The accuracy of the proposed model is about 99.02%. The HFIPO-DPNN framework can be enhanced for predicting the dropout for students with other disabilities. The optimization showed that factors influencing education other than familial factors are to be considered in the prediction of dropout.**

***Index Terms*—Education, dropout, physically impaired, feature selection**

I. Introduction

Education has a pivotal role in uplifting people and possesses cutting impact on all aspects of life as it forms an investment for human and economic development [1]. Especially for those people who are physically impaired, education is the only way that can uplift them to have a better life. The average dropout of normal students in their secondary is about 36.5%, 38.5%, and 8.6% among the Hispanic, Afro American, and Asian ethnicity respectively [2]. There are several factors that lead to the dropout of students from schools and colleges. The initial studies concentrated on the factors related to students. However, many researchers suggested that the family factors like poor economy and single parent are found to be the dominant risk factors along with poor student's performance [3]. When the student is physically impaired, the risk factors multiple in larger magnitudes. The challenges involve learning with teaching response, accommodation, and curriculum adaptation [4]. Especially according to the 2011 census 45% of disabled populations in India are remained to be illiterate, related to 26% of Indians. Physically disabled students have higher dropout rates, with 59% of educated people with disabilities in regular Class X, compared to 67% of the population [5]. Early precise prediction on students' performance with their current performance records is crucial for efficiently performing essential pedagogical interventions for ensuring students' satisfactory graduation within the course period [6]. The predicting task gets complex by the ever-expanding data with the student enrolments and continuous shifting of student characteristics [7]. Additionally, this model may guide the students on a particular path to select appropriate options that can fulfil them in their life rooted on the past experience of students [8].

With the earlier prediction on dropout the organization or institutions can take the necessary steps to prevent it from occurring. Rooted on the earlier works, it is observed that the deep learning algorithms can provide better performance in predicting the dropout. Hence a novel HFIPO-DPNN framework is proposed with the hybrid firefly and improved particle swarm optimization (HFIPO) and Dropout Prediction neural network (DPNN).

The articles numerous issues arise for students with various impairments during their time in higher education. Due to this reason, some potentially impaired students choose not to enroll in higher education institutions or do not complete their degrees. Students with physical disabilities frequently struggle to organize and store the supplies they need for class. Many schools hire a teacher's assistant to assist them in using this technology and have it prepared before each class. The biggest obstacles to providing educational services to kids with impairments seem to be the following: The educational system still harbours unfavourable attitudes and prejudices toward students with impairments. It may be challenging for students with disabilities to receive educational services equitably if certain educators, staff members, and students lack awareness of and sensitivity to disability concerns. Physical barriers, such as heavy doors, non-accessible restrooms, non-accessible transportation to and from school, and the absence of ramps and/or elevators in multi-level school buildings, continue to prevent students with disabilities from accessing educational programmes. Finding accessible student accommodation is a challenge for post-secondary students as well. Students may have a variety of disabilities, including mental illness, cerebral palsy, mental retardation, hearing impairment, and locomotor disability, children that struggle with learning.

Research Questions:

1) How is the data collected for analysis?
2) What are the attributes/features considered for prediction

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purposes?
3) How is the prediction carried out?
4) What are the measures considered for evaluating the proposed model?

In the proposed model, the data on the students' performance and their family background is taken for the dropout prediction. So that it will be helpful for the professors to give special training to students rooted in dropout status.

The contributions of the projected work are listed below:

- To introduce a new hybrid firefly and improved particle swarm algorithm to optimize the feature selection that influences the dropout of hearing-impaired students.
- To predict the student dropout rooted in the previous semesters' marks with a novel HFIPO-DPNN.
- The Dropout Prediction neural network (DPNN) is trained with hybrid firefly and improved particle swarm optimization (HFIPO)

The other sections of paper are provided rooted on the proposed HFIPO are abridged as follows: In Section II, the works related to the dropout prediction study and the neural network model used are studied, and Section III explains the mathematical working of the proposed HFIPO-DPNN. Section IV provides facts about HFIPO-DPNN in terms of the neural network model and mathematical expressions for feature selection, Section V exhibits the proposed framework result rooted in the performance. The final section provides the conclusion and lists the future scope.

II. Related Works

A. Literature Review

A study was conducted to categorize and predict the academic performances of a group of students over a period of 6 years using multiple features collected from an academic organization. The study enabled the researchers to determine an estimated grade that a particular student would obtain in a certain course and devise improvement methodologies accordingly through training [9]. The study showed equal dependence of the student's performance on academics, personal, social, and extra-curricular activities. Machine learning algorithms 'Na ïve Bayes' (NB) and 'Decision Tree' were opted for the classification of data. Initially, data were collected through the survey and pre-processed for data mining tasks for generating the student's performance prediction model [10]. A different classifier models were used to foretell dropouts in an online course with 10-fold cross-validation. It was established that the accuracy of 79.7%, 73.9%, 87%, 76.8% for decision tree, NB, nearest neighbor, and neural network, respectively [11].

Analyzing a student's performance using NB classifier is one of the classification methods used to recognize hidden relations between subjects in Sijil Pelajaran Malaysia. The algorithm can be implemented for performance classification during the early stage of 2nd semester achieving an accuracy of 74% [12]. Works implemented in [13] involved building a recurrent neural network (RNN) for forecasting students' final grades from log information in education systems. A log information basically provides details of learning activities of all the students who used the LMS, the electronic book system, and the electronic portfolio system. A comparable prediction accuracy was noticed in this work that used log information to predict final grades [13]. RNNs had been employed for evaluating the results through game activity [14], and to forecast answers to queries of numerous skills with historical data [15].

A novel data mining approach was proposed with a recommender system (RS) for forecasting student performance. For validating the approach, it was compared logistic regression-based RS techniques. Experimental outcomes presented that the suggested method can increase prediction effectiveness [16]. The work presented a methodical literature review that signifies the usage of machine learning algorithms in RS and categorizes study prospects. The study determined that Decision Tree and Bayesian algorithms are extensively employed in RS and it offered new prospects for researches [17]. Various data mining algorithms formed from a combination of classification, clustering algorithm, association rule algorithm, and many more were investigated to determine the most superior combination. The study indicated the highest efficiency in combining clustering and classification with association rule algorithm for building a recommendation engine to recommend courses in E-learning [18].

Using Artificial Neural network model, Abu-Naser *et al.* [19] in 2015 attempted to predict the performance of sophomore students and tested it. The factors influencing their performance were listed as freshman year scores in all subjects, especially in maths and electrical circuits along with high school scores. They developed the Multilayer Perceptron Topology model, which predicts 80% of students' performance accurately. Using the same model, Zaccharis in 2016, predicted academic performance. But it was rooted in learning activities, email communication, interaction, collaboration, and through online quiz. Here the model predicted the results with the classification accuracy of 98.3% [20].

In 2017, Castro *et al*. indicated that ML techniques such as Bayesian and decision tree were stable, whereas neural network approaches were more effective and serves a complementary role in identifying the students who are in need of assistance [21]. Students attending sophomore courses were analysed to predict the students prone to failure. To reduce the number of failures and to increase the learning activities, Sukhbaatar et al in 2019, attempted this study. They used a simple 3-layer neural network to predict the failure status. By the final week, 65% of students were predicted accurately.

B. Motivation

Physically challenged worldwide, student dropout is a severe issue. It has an impact on the dropout as well as their previous school, family, and society at large. Big data is promoted as the most important technology in data analysis given the state of science and technology today. Effective dropout prediction for students with physical disabilities based on educational data is now a hot research issue. Previous research has only examined student dropout rates at particular stages, such as the individual, middle school, and university. However, there hasn't been much study done on using machine learning techniques to forecast university dropout rates for physically challenged students using unusual datasets.

C. Problem Statement

Some of the biggest obstacles facing hearing-impaired pupils are a lack of qualified sign language instructors and the expensive expense of assistive technology. These kids used emotion-focused coping techniques to get through social obstacles, whereas problem-focused coping strategies are used to tackle academic challenges. Social support networks were utilized by visually impaired and hearing-impaired students more frequently than other coping mechanisms, yet this assistance would prove ineffectual if the students themselves did not put in any effort. Due to the visual character of graphs, charts, tables, and plots, students who have visually challenged experience particular difficulties when learning mathematical ideas. While touchscreens have been investigated as a potential tool to help those who are visually impaired understand mathematical concepts, many of these devices are not freestanding, weren't created with a user-centered design approach, and weren't tested with users who are visually impaired.

From the study of related works, various data produces various results were found. In this study, the HFIPO-DPNN method is used to predict the dropout of the student with the help of their previous marks and high school scores for the betterment of accurate prediction.

III. Preliminaries

A. Selecting the Features

The selection of supervised features is mostly focused on the problem of labeling, and the significance or association between the function and the class category is used as its basic concept. Relevance evaluations may determine the significance of the features. This model aims to find an optimum function group for a training sample with characteristics and class labeling that provides the maximum accuracy of the classifier.

A general structure for selecting features is the Hilbert-Schmidt dependence criteria as seen in the equation, where *J(S)* tests the dependence of a number of data on *C*. The principle of this paradigm is that *J(S)* should be maximized by the key frame subset, which converts the choice of features into more of an optimization method.

$$D = \arg\max[J(S)]$$

The filter method typically uses assessment criteria to increase the correlation between the function and the class labeling and to decrease the correlation between features. In addition, the association between features is often superseded by redundancy.

Generally, rooted in the type of output, feature selection method is divided into two, weighted ranking method and subset selection model [19]. Apart from this filter model (which considers the relation between features and output labels), wrapper model (takes the error rate or accuracy in the standard of evaluation), and embedded model (selecting features in the training model and generating output) is commonly used. Its performance is measured by machine learning model. Lasso (Least absolute shrinkage and selection operator) is commonly used to reduce the sum of squares of residuals if the absolute values of the regression coefficient.

B. Improved Particle Swarm Optimization (IPSO) Algorithm

The Particle Swarm Optimization (PSO) is a well-known optimization algorithm that is framed rooted in the natural swarm of flocking birds. The IPSO [22] is constructed on the fundamental concept of positioning the particles and their velocities. The features along with its datasets are initially located in the search space. The data position vector is provided as in Eq. (1).

$$o_i = \left(o_{i1,} o_{i2,} o_{i3,} \dots \dots \dots \dots, o_{iS}\right) \quad (1)$$

In Eq. (1), *S* is the Search space dimensionality and *i* is the feature set. In the PSO, the particles are always under motion and hence possesses the velocity *V* and its vector can be represented as in Eq. (2).

$$v_i = \left(v_{i1,} v_{i2,} v_{i3,} \dots \dots \dots \dots, v_{iS}\right) \quad (2)$$

The particle continuously updates its velocity and position rooted on the nearest swarm particles. Each particle records are the previous position as the personal best and the population generates the best position to be the global best wihch are termed as the $pbest_i$ and $gbest_i$ respectively. From the obtained best positions, the search for the optimum solution continues with updating of position and velocity with the following expressions in Eqs. (3) and (4).

$$o_{is}(t+1) = o_{is}(t) + v_{is}(t+1) \quad (3)$$

$$v_{is}(t+1) = wv_{is}(t) + C_1R_1\left(pbest_i(t) - o_{is}(t)\right) + C_2R_2\left(gbest_i(t) - o_{is}(t)\right) + C_3R_3(gbest_i(t) - pbest_i(t)) \quad (4)$$

where,

'C_1'and 'C_2'are acceleration coefficients,

'w' = inertial weight (constant),

'R' = a random number in the range [0, 1],

'$pbest_i(t)$' = best position experienced by particle i until time *t*,

'$gbest_i(t)$' = best position discovered by the swarm until time *t*

'i' = variable of a *D*-dimensional vector of position or velocity.

Since the inertial weight is highly responsible for balancing the exploration and exploitation rates of the algorithm, it is considered to have a high impact on the direction of particles in the problem space. Exploration is defined as the property of swarm intelligence and the evolutionary computing method that is popularly preferred at the initial stages of a process to find new solutions in problem space. The $pbest_i$ and $gbest_i$ will be updated as follows:

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if f(xi(t+1)) ≥ f(pbest_i(t)),
    pbest_i(t+1) = pbest_i(t)
otherwise,
pbest_i(t+1) = x_i(t+1)
where, f(xi) is the fitness value of
particle i.
To calculate gbest,
gbest_i(t+1) = min f(pbest_i(t+1))
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It is generally the case for the diversity of the particles at initial steps to be high and then slowly decrease over the optimization processing time.

C. Firefly Algorithm

Firefly is another nature inspired algorithm developed with its attractive characteristics that are represented as the illuminative function [23]. The algorithm can be described through its three fundamental functions namely, attraction towards partners, attraction towards prey, and its mechanism of warning. Firstly, the light intensity at a specific distance 'r' from a light source obeys the inverse square law which means, as the distance 'r' from the light source increases, the brightness 'I' tends to decline, i.e. the light source is inversely proportional to the squared distance. The second aspect influencing the visibility of fireflies is that light is absorbed by the air, which gets weaker as when the distance is increased. Initially, the light intensities are formulated and rooted on it the attractiveness of the firefly is generated for the given data as in Eqs. (5) and (6)

$$I = I_0 e^{-\gamma r_{ij}^2} \tag{5}$$

$$I = B_0 e^{-\gamma r_{ij}^2} \tag{6}$$

In Eqs. (5) and (6), I_0, B_0 are the initial light intensity and attractiveness constant of fireflies respectively, γ is the light absorption coefficient (=1). The distance between the two fireflies is r_{ij}, which is given as in Eq. (5).

The best solution obtained from the firefly algorithm is represented in the Eq. (7) as:

$$o_i = o_i + B_0 e^{-\gamma r_{ij}^2}\left(x_j - x_i\right) + \alpha(rand - 0.5) \tag{7}$$

where, the second term of the equation is due to the attraction and the third term is randomization with 'α' being the randomization parameter. '*rand*' indicates a random number picked from a uniform distribution in the range [0, 1]. Similarly, the expression (*rand* − *0.5*) represents the range [−0.5, 0.5] to incorporate a positive and negative variation. β_0 is always set to 1 and $\alpha \in [0, 1]$.

IV. Proposed Methodology

The present prediction system is structured with the novel DPNN along with the hybrid improved Particle Swarm and Firefly optimization algorithm. In the proposed methodology, initially the dataset was pre-processed by removing inexactness and normalized through the Min-Max Normalization Technique, where min and max are the minimum and maximum of each input features (i.e. 0 and 1 respectively).

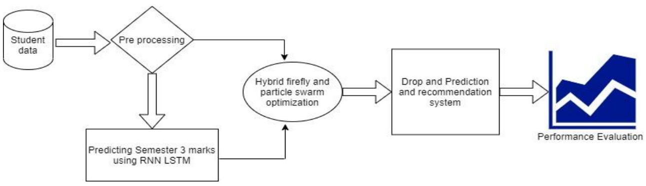


Fig. 1. Proposed HFIPO-DPNN.

Initially, using the collected data, the 3rd semester marks will be predicted. The obtained pre-processed data along with the predicted 3rd semester marks is provided to the novel HFIPO algorithm for optimizing the features. The optimized features are provided for the novel DPNN. The proposed DPNN model is trained with 80% of the dataset. Subsequently, the trained model is then tested with the complete dataset. The proposed HFIPO-DRP-NN framework for predicting student dropout prior to the final semester exams is given in Fig. 1.

For the HFIPO modelling, firstly, a set of particles in *D*-dimensional space within the range of [0,1] is generated, where '*D*' denotes length of the original feature vector. If the value of the decision variable is higher than a predefined threshold value, then the corresponding feature element will be selected; otherwise, it will be removed from the original feature set. Further, the best subset of features is explored by the particle set in the search space. Every iteration involves the updating of the velocity and position of each particle, the best experience of each particle, and the best experience of swarm. Despite finding the distance between firefly 1 and firefly 2, the proposed work calculates the distance between firefly 1 and $gbest_i$.

$$r_{ij} = \|x_j - x_i\|,$$

where, x_j and x_i are firefly 1 and firefly 2 respectively. The distance between any two fireflies x_i and x_j is expressed as the Euclidean distance by the basic Firefly algorithm.

$$r_{ij} = \|x_j - gbest_i\|$$

$$r_{ij} = \sqrt{\sum_{k=1}^{d}(x_{i,k} - gbest_{i,k})^2}$$

Then the position is calculated as,

$$o_i = o_i + B_0 e^{-\gamma r_{ij}^2}\left(x_j - gbest_i\right) + \alpha(rand - 0.5)$$

In this model, embedded feature selection technique is used. This is the combination of filter and wrapped methods as discussed in Section III. This model reduces over fitting by regularization techniques. This technique works by penalizing the magnitude of feature coefficients and helps in minimizing the error rate over the iterations.

A. Data Collection

The Physically impaired student data is collected exclusively from the ITI institution in and around Bangalore. The dataset consists of several features like family background, academic performance during the final schooling, and also the first two semester marks obtained by every individual. Additionally, the level of impairment is also specified in Table I.

TABLE I: Feature from the Collected Data

S.no	Features	Datatype	Values
1	Sex	Character	M,F
2	Family Size	Integer	Between 1 to 6
3	Family Income	Integer	0,1,2,3 (0-BPL,1-poor, 2-Average, 3-High)
4	Age	Integer	16 to 25
5	Subject	String	Fitter, Mechanic,Turnar,etc
6	Medium of Instruction	String	Kannada, Tamil, English,etc
7	Kannada	Integer	0 to 100
8	Maths	Integer	0 to 100

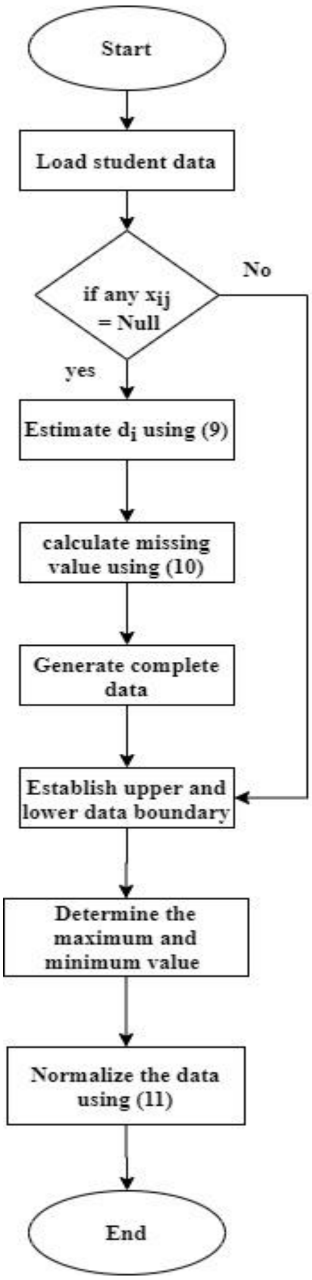
9	Science	Integer	0 to 100
10	Social Science	Integer	0 to 100
11	Percentage	Integer	0 to 100
12	Sem I Percentage	Integer	0 to 100
13	Sem2 Percentage	Integer	0 to 100
14	Difficulty level in understanding	Integer	0 or 1 (Based on Maths and science subject)
15	Disability Status	Integer	0 or 1

B. Preprocessing and Normalization

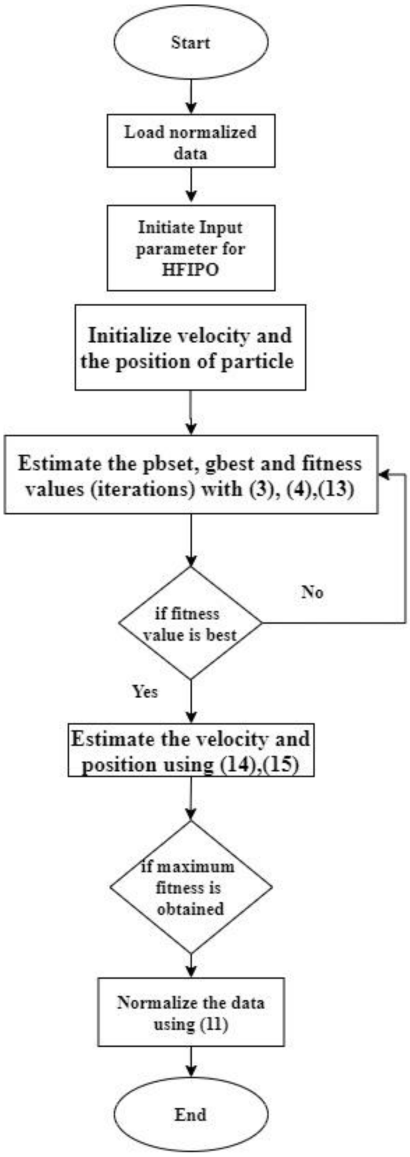
The collected data consists some missing values that provide some ambiguity in utilizing the data for the present work. This method computes the missing value from the measured values from the data through the Eqs. (8), (9). Fig. 2 shows the Flowchart for (a) preprocessing and normalization and (b) feature selection with HFIP.

$$d_i = \sqrt{(P_{xi} - K_{xi})^2 + (P_{yi} - K_{yi})^2} \tag{8}$$

$$M_{vi} = \frac{\sum_{i=1}^{n} \frac{M_i}{d_i^2}}{\sum_{i=1}^{n} \frac{1}{d_i^2}} \tag{9}$$



(a)



(b)

Fig. 2. Flowchart for (a) preprocessing and normalization and (b) feature selection with HFIP.

In Eq. (9), M_{vi} is the missing value, M_i is the measured value, d_i^2 is the k powered distance (*K=2*), n is the total data in each feature, P_{xi}, P_{yi} are the position of missing value in *x* and *y* axis. Similarly, K_{xi}, K_{yi} are the position of known value in *x* and *y* axis

The complete dataset obtained through the IDW is normalized through the min-max normalization technique. The mini-max is generally a linear transformation technique in which the data is transformed with a pre-defined boundary [24]. The normalized data is obtained through Eq. (10).

$$D' = \left(\frac{D - D_{min}}{D_{max} - D_{min}}\right) \times (U - L) + L \tag{10}$$

In Eq. (10), D' and D denote normalized data and actual data, D_{min} and D_{max} are the minimum and maximum value in the dataset for each feature. U and L are the predefined upper and lower boundary values.

C. Recurrent Neural Network with BiLSTM Layer

Recurrent neural systems have a directional loop that can retrieve and relate past data to the actual output, which is the key qualification in RNN. Moreover, the output is known as the current output of an arrangement, and the nodes between the hidden layers are never connected. In the present framework to predict the final semester marks Bi-LSTM-RNN network model is used, which includes input layer, output layer, 4 hidden layers (including BiLSTM).

This model is activated by sigmoid activation function and optimized using adam optimizer, which used the magnitude of the gradients and normalizes it. This facilitates the prediction of final semester marks. This helps in increasing the learning rate and stimulates rapid convergence. The mathematical expression for rmsprop optimizer is as follows:

$$b = b - \alpha \bullet \frac{db}{\sqrt{vdb} + \varepsilon}$$

where, *db* represents acceleration, *vdb* represents velocity, α and ε are hyper-parameters.

D. Optimization in Feature Selection

HFIPO algorithm.

In the present framework, a novel optimization algorithm is formulated with IPSO and Firefly algorithm to select the optimum feature from the student dataset. The normalized dataset is initially fed into the PSO and its outcome is processed through the firefly algorithm to obtain the optimized feature that can influence the dropout of the student from their education. The primary objective of performing this optimized feature selection is to decrease the number of input features taken for DPNN, which can further result in the reduction of training and processing time and improvisation of its recommendation accuracy as well.

Initially, the weight of the IPSO algorithm is estimated through Eq. (11) as

$$w = w_i - \left(\frac{w_i - w_f}{iterationmax}\right) \times iteration \tag{11}$$

The data are processed through the IPSO using Eqs. (1) and (2), the obtained *gbest* value is compared for its fitness values over the *pbest* value of individual particles and the final fitness is established with Eq. (12).

$$f(i,t) = \begin{Bmatrix} true, if\ fitness(particlei\ t\ )gbest^{t-1} \\ false, if\ fitness(particlei\ t\ ) > gbest^{t-1} \end{Bmatrix} \tag{12}$$

The position of the particle and its velocity is estimated through the following expression in Eqs. (13) and (14) with the saved temp variable (X_{i_temp})

$$O_i(t+1) = O_i(t) + B_0 e^{-\gamma r_{ij}^2}\left(Xi\ (t) - gbest^{t-1}\right) + a \in_i \tag{13}$$

$$V_i\ (t\ +\ 1)\ =\ O_i(t\ +1)\ - X_{i\_temp} \tag{14}$$

E. Prediction of Dropout

The architecture of the Dropout prediction neural network model is shown in Fig. 3. The optimized data is segmented in the ratio of 80% and 20%. The 80% of the data is fed into the DPNN for training the prediction of student dropout. In the proposed model DPNN has input layer (Il) one hidden layer and one output layer (Ol). Two different activation functions are used for the hidden layers as F1 and F2. Relu and Sigmoid activation function and adam optimizer are used to optimize the prediction accuracy. The mathematical representation for each layer is given as,

Input layer:

$$I_i^t(t) = H_j^1(t-1) \tag{15}$$

Hidden layer 1:

$$H_j^1(t) = F_1\left(\sum_i^n V_{ij}^1\, x_i\ (t) + \left(u_{ij}^1 I_1^t(t)\right)\right) \tag{16}$$

$$H_k^2(t) = F_2\left(\sum_i^h V_{jk}^1\, H_j^1(t) + \left(u_{jk}^1 H_1^t(t)\right)\right) \tag{17}$$

Output layer:

$$O_k(t) = F_1 \sum_g^m W_{gk}\, d_g^2\ (t) \tag{18}$$

The fitness functions are given by

$$F_1 = \frac{1}{1+e^{-i}} \tag{19}$$

$$F_2 = \frac{e^{2i}-1}{e^{2i}+1} \tag{20}$$

where *V*, *u*, are the weight of the first and second hidden nodes and *W* is the weight between the hidden and output layer, and *i*, *j*, *k* be the nodes at hidden layer1, hidden layer 2, and output layer. At the termination of the training process, the novel DPNN Prediction model is constructed. The test data is provided to the generated model to evaluate the performance of the dropout prediction.

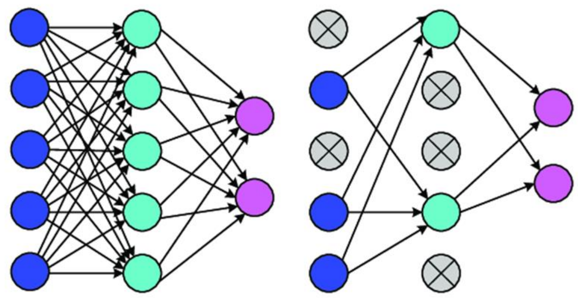


Fig. 3. Dropout prediction neural network model.

F. Evaluation

This section presents a comparative analysis of the performances of the proposed and existing methods. The classification accuracy is calculated by using:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Sesitivity = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$f1\ score = 2 * \frac{Sesitivity * Precision}{Sesitivity + Precision}$$

In HFIPO, in-order to produce an algorithm convergence in early generations, a random number is set to the inertia weight.

where,

TP — True Positive: the number of students that were predicted to be passed and actually passed the exams

TN — True Negative: the number of students that were predicted to be passed but gets dropped out

FP — False Positive: the number of students that were predicted to be dropped out and actually dropped out

FN — False Negative: the number of students that were predicted to be dropped out but passed the exam

V. Result and Discussion

The proposed work has been implemented in Matlab. The data must be collected from 250 physically impaired children belonging to ITI institute, Bangalore. The data has been collected manually. The data is used for the current prediction model that contains 1,00,000 instances of student details over the feature presented in Table I. The proposed model is implemented in python language. Using Bi-LSTM RNN model, the semester 3 marks are predicted with RMSE of 0.17. The pre-processed data along with predicted semester marks is given to the hybrid optimization model. The features selected are evaluated based on the percentage of the dropout impact. For the family size, the impact on dropout is 74%, for subject the impact on dropout is 59%, for a medium of instruction the impact on dropout is 72%, for Kannada the impact on dropout is 63%, for social science the impact on dropout is 100% and so on. Table II clearly explains the percentage of impact for the selected features.

TABLE II: Feature Selected Through the Optimization Algorithm

Features	% Impact on dropout
Family Size	74%
Subject	59%
Medium of Instruction	72%
Kannada	63%
Social Science	100%
10th Percentage	88%
Sem 1 Percentage	92%
Sem 2 Percentage	100%
Sex	75%
Family Income	86%
Age	73%
Maths	96%
Science	94%
Difficulty level in understanding	90%
Disability Status	62%

The proposed HFIPO-DPNN framework was evaluated for its performance on various performance metrics as sensitivity, specificity, accuracy, and F1 score that are computed through the confusion matrix. The obtained results (in terms of sensitivity, specificity, accuracy, F1-score) are plotted according to their values in Fig. 4.

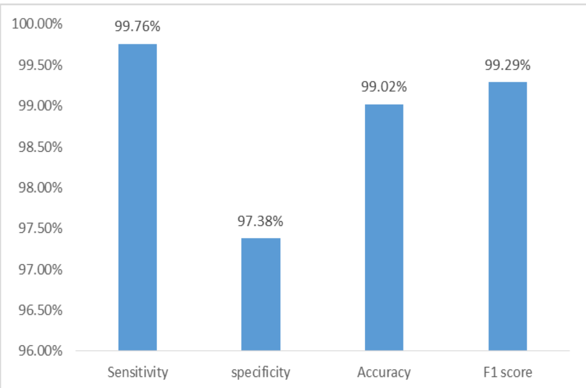


Fig. 4. Performance of the proposed HFIPO-DPNN.

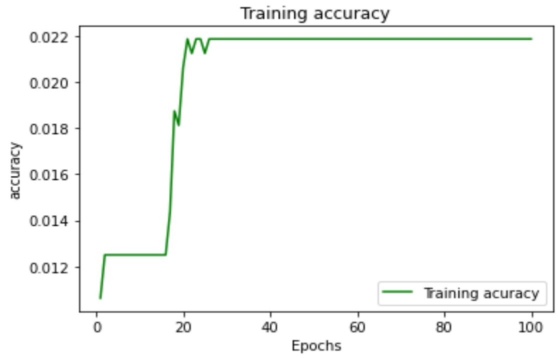


Fig. 5. Accuracy of the proposed HFIPO-DPNN model.

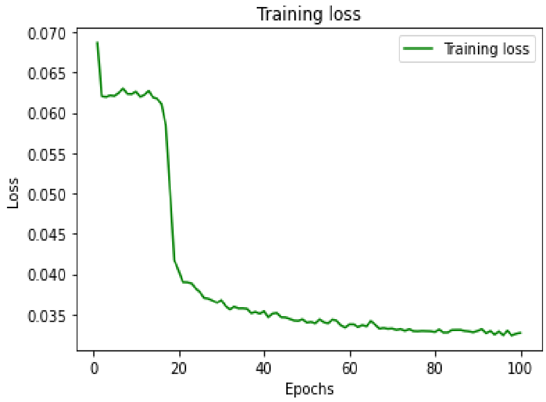


Fig. 6. Loss of the proposed HFIPO-DPNN model.

The results recorded in terms of accuracy is shown in Fig. 5. The accuracy level in the graph points to the overall prediction accuracy in terms of dropout rate of physically impaired students. The loss function has been computed in terms of root mean square error. The accuracy of the proposed Prediction model is about 99.02%. The specificity and the sensitivity of the proposed framework are 97.38 % and 99.76% respectively. The F1 score for the proposed framework is about 99.29%. The loss of the proposed model is shown in Fig. 6.

The proposed HFIPO-DPNN is compared with the rule and decision tree [25] based dropout prediction model. The proposed framework has the higher accuracy than the existing models in predicting the dropout of students. The comparison of performance is given in Fig. 7.

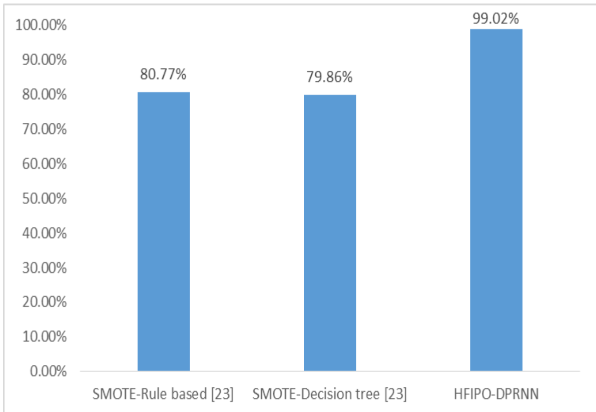


Fig. 7. Comparison of accuracy over the existing model.

VI. Conclusion

The prediction on the dropout of the students prior to exams to decrease the dropout rate by giving special training was achieved through the proposed HFIPO-DPNN model. The study is carried out specifically towards physically challenged students through synthetic data. The data set is initially preprocessed to remove the data ambiguities followed by normalization. The normalized data is processed through the HFIPO algorithm to select the optimized feature to predict the dropout of students from their education. The optimized feature set data is fed into the novel DPNN with two distinct active functions for four hidden layers. The output of the neural network helps to adapt precautionary steps to help the students to score the exams. The proposed framework is evaluated for its performance on various metrics. The proposed model attained the accuracy of about 99.02%. Future work may involve the robust recommender model with higher accuracy with several other factors that may influence the performance and dropout of physically challenged students from their education.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Ms. Marina. B and Dr. A Senthilrajan conceived of the presented research. Ms. Marina.B carried out the Data collection, implementation, and written the manuscript. The ideology for the implementation is provide by Dr. A. Senthilrajan. Both the authors discussed the results and commented on the manuscript. The carried-out research is supervised by Dr. A Senthilrajan.

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