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PREDICTING THE PERFORMANCE IN SEMESTER AND TO IMPROVE THE STUDY SKILLS OF HEARING-IMPAIRED STUDENTS IN SPECIAL EDUCATION USING RNN-HFP

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ABSTRACT

Education was one of the fundamental need and rights for all people across the world. Every government formulates different schemes to ensure education for all as it results in the countries growth on various aspects. The people who are physically impaired (PI) are also included in these aspects. The performance of those students requires continuous monitoring to acknowledge their attention towards studies and to guide them towards better academic achievements. In this paper, the Recurrent Neural network (RNN) and Hybrid firefly – particle (HFP) algorithm based novel predictor is proposed to predict semester performance of the hearing-impaired students. The RNN algorithm predict the performance of the student and HFP is involved to optimize the prediction performance that may suffer from convergence error. The proposed model was evaluated for its accuracy at both the testing and training phase. The model was initially trained with 80% of data and tested with 20% of it. The proposed model was evaluated for its accuracy at both the testing and training phase. The outcome showed that the MSE loss in training is 0.05 with testing RMSE value of 0.24. The proposed model can be enhanced to predict the drop out probability for the PI students in future.
Keywords: *Accuracy, Hearing Impaired Students, RNN-HFP, Prediction Model*.

1. INTRODUCTION

Education is recognized as a dominant tool of social alteration and frequently starts ascending measure in the social structure, thus assisting to bond the gap among the different society [1]. Also, according to the report [2], requirements for handicapped education are an essential measure for the national education system, which was to be managed by the Department of Education. Conferring to official assessments from the Census of India (Government of India, [3]), there were nearly 26 million (2.1%) disabled people in the country. The Government has generated several strategies for special education since independence.

Besides, inclusive education is presented for all students. According to UNESCO report [4],

inclusive education gives children the right to study with their peers in the schools around them, regardless of their abilities.

However, inclusive education may not fully meet the needs of hearing-impaired students in general schools without adapting instructions to their specific strengths and needs and incorporating the curriculum and school context

which are accessible to these students without imposing them into traditionally delivered curriculum [5]. Since, disabled students have educational needs which differ from those of other students, with both physical and mental disabilities causing difficulty in learning [6].

In addition, physically impaired students face particular challenges in higher education regarding the accommodation and adaptation of curriculum, teaching, assessment, and learning. These reasons become the criteria of eligibility to examine the higher education ability to comprise diverse learners [7]. Hence, for improving these students learning, researchers use technology-supported tools to adapt disabled students' learning environments with their learning performance. The use of applications like technology- supported special education has steadily increased during these days [8]. To improve their learning, students' understanding of their disability must be analysed, and how these create effect on their academic performance (self-awareness) and knowledge on requesting accommodations (self-advocacy) have interlinked without various results on higher education along with performance, persistence and satisfaction [9].

Moreover, people with disabilities seek post-secondary education and training for satisfying careers and stable incomes. Unfortunately, students with disabilities face various challenges can lead to lesser graduation desirable college which is lower rates than of students with no other disabilities. As a consequence of this disparity, there is growing interest in topics that assess the academic achievements of students with disabilities [10]. However, investigation and analysis in the application and development trends of the integration of technology in special education is still lacking.

Hence there is a clear need for the prediction system to forecast the performance of the physically impaired students through which the students can be encouraged to perform better and they can be provided the necessary supports for their improvement in higher education. The ANN (Artificial Neural Network) based model is presented for predicting the academic performance of engineering students [11]. Multi Adaptive Neuro-Fuzzy Inference System with Representative Sets based model is predicted student's future performance after entering into university education [12]. From the earlier research, it was evident that the neural network provides enhanced prediction performance than other machine learning algorithms. However, the neural network suffers from the local solution or it does not provide perfect weight associations for the best solution. For this purpose, to predict the semester mark for the Hearing impaired students, the RNN and hybrid Firefly and Particle Swarm Optimization (HFPSO) Algorithm based novel prediction model is proposed in this paper. This novel predictor model is named as RNN-HFP. Here, HFPSO algorithm is used to optimize the process of feature selection process for enhancing the performance of proposed model.

The rest paper is organized as follows: Section II is reviewed the related research papers. Section III is discussed the research methodology of the paper. The outcomes and argument of the paper are discussed at Section IV. At last, the paper will be concluded at Section V.

2. LITERATURE SURVEY

In this section, the related literatures are reviewed. It is mainly focus on the education performance of hearing impaired students.

Cupples et al. [13] had analysed language and speech results on young children who are having hearing loss and additional disabilities. Direct assessment and caregiver report are used to analyze the accurate output of receptive and expressive language skills and speech. Entire participant cohort and analyzed the outcomes of children with hearing aids (HAs) versus cochlear implants (CIs). The population-based cohort nearly 146 children in the age of five with hearing loss and additional disabilities were examined. Overall participants, the multiple regressions witnessed that better language results are related to milder hearing loss, use of oral communication, higher levels of cognitive ability and maternal education and earlier device fitting. Speech output accuracy is related to the oral communication use. The outcomes of HA users took after entire cohort. The CI users are prominently related to the good language outputs with the help of oral communication and higher cognitive ability levels.

Chao, Pen-Chiang [14] had proposed the study that assesses the correlation and predictive relationship along with self-determination and betterment of disabled students' college life Subjects were 145 senior college students enlisted from northern Taiwan between the age of 22 and 25. Their disabilities may differ, like visual impairments, hearing impairments, speech/language impairments, physical impairments, specific learning disabilities, emotional and behavioral impairments, one or more disabilities, autism and health impairments. The correlation between SDSCS and WHOQOLBREF are assessed with the help of Pearson correlation and stepwise multiple regression analyses. Also, results assured positive correlations among self-determination and life betterment. Moreover, this research underlined not only about instant influence in the quality of disabled person's life, but also the long-term impact.

Cheng, Sanyin [15] had explored the study of the change in thinking styles of hearing-impaired students in art and design academic discipline. In the meantime of one academic year, Thinking Styles Inventory-Revised II had administered twice for 129 first-year students and 127 second-year students with

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hearing-impairements. The outcome exclaimed about Type I thinking styles (more creativity-generating, less structured, and complex) and Type II thinking styles (more norm-favouring, more structured, and simplistic) had been demonstrated to hearing impairment students with huge preference. Overall, changes in style may vary from university class levels to gender. Additionally, following interview assured that acculturation influence modifies the styles of hearing-impaired students modified. Also, it also discussed about contributions, limitations, and implications of recent study on inclusive/mainstreaming higher education.

Cheng, Sanyin, and Kuen-Fung Sin [16] had goals on exploring the problems of university self-efficacy in relation to the students' life betterment about 15 hearing impairment and hearing students mainly from China. The demographic sheet, the University Self-efficacy Scale, and the Quality of University Life Measure (QULM) administered 350 hearing impaired students and 463 hearing students. Multiple regression analyses were accomplished individually on every university quality 20 life scales, with all university self-efficacy scales acting as predictor variables on every analysis and controlling the relevant demographic variables. The results showed that university self-efficacy was an important and positive evaluation of the university life quality to all participants.

Amrieh et al. [17] suggested a students' performance prediction model through data mining approaches with selected features known as student's behavioural features. The proposed model was assessed in three diverse classifiers; Decision tree, Artificial Neural Network, and Naïve Bayes along with ensemble methodologies such as Bagging, Boosting, and Random Forest. The proposed model accomplished up to 25.8% accuracy after using the ensemble methods which was elevated than accuracy when features of behavior were removed.

Vandamme et al. [18] used neural networks, decision tree and linear discriminate analysis for making early academic predictions on students' success in their inaugural year at university. Yi et al.[19] suggested a supervised deeplearning based neural network(DL) model to estimate link based traffic flow conditions. The model had three hidden layers to get 99% accuracy while predicting the congestion.

Bendangnuksung et al. [20] suggested a DL model for predicting the students' performances. In this setup, it was recognized that a DL model is able to execute much better, even with less amount of training data because of the quality of dataset provided to it and it got 84.3% accuracy.

Agrawal et al. [21] used traditional machine learning algorithms like Rule induction, Random forest, Naïve Bayes and Decision Trees. They got the accuracies of 90%, 85%, 84% and 82% respectively with Decision trees, Random forest, Naïve Bayes and Rule induction.

Veeramuthu et al. [22] used three modules. The first module has classification techniques to infer student's academic performance. The second module will be clustering the students based on their e-learning cognitive styles. The third module enabled teachers to differentiate the students based on their academic potential so that weak students get more attention.

Yadav & Pal [23] implemented Educational Data Mining Techniques to make a prediction model of engineering student's performance. The ID3, CART, and C4.5 algorithms of decision tree were executed to predict performance in their completion exam. This result can be employed to forecast on the students' performance next year. Originally 90 students data with 13 variables are used in the study and attributes of final exam grades were used. The result showed that ID3, CART, and C4.5 algorithms provided an acceptable accuracy level, C4. 5 method outclassed the rest with 67.7778% accuracy.

Naïve Bayes(NB) classifier could recognize the hidden data between subjects that influenced students performance in Sijil Pelajaran Malaysia. The NB algorithm was used for classification of student's performance in early stages of 2nd semester with 74% accuracy [23]. A recurrent neural network (RNN) approach was proposed for forecasting students' final grades from their learning activity in education systems. The collected data indicated the presence of activities such as student utilizing LMS, electronic portfolio system and the electronic book system. By using this approach to get data from students, this experiment investigated the accuracy of prediction [24]. RNNs had been employed for evaluating the results through game activity [25], and to forecast answers to queries of numerous skills with historical data [25]. From the study of related works, various data produces various results were found. In this study, HFIPO-DPNN method is predicted the student's dropout with the help of their previous marks and high school scores for the betterment of accurate prediction.

Student's performance examined using NB classifier which is one of the methods of classification to recognize the hidden data between subjects that influenced students' performance in

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Sijil Pelajaran Malaysia. The naïve Bayes algorithm can be employed for classification of performance of students in early stage of 2nd semester with 74% accuracy [23]. A recurrent neural network (RNN) approach was proposed for forecasting students' final grades from the log information in education systems. The log information indicated the activities of learning of students who utilizes the LMS, the electronic book system and electronic portfolio system. This research used this approach to get data from students and investigated the prediction accuracy [24]. RNNs had been employed for evaluating the results through game activity [25], and to forecast answers to queries of numerous skills with historical data [25]. From the study of related works, various data produces various results were found. In this study, 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.

Sathya Durga v (2020) [26] implemented enhanced pso algorithm to build a Academic performance prediction model for deaf students. The data set for this research work was collected from deaf students all over Tamil Nadu. PSO From the given data set to select the minimum number of features to build a prediction model was found by running RBPSO algorithm. The number of features needed by the model was found to be 7. Neural Network build with the RBPSO algorithm achieved a low 128 error of 0.098.

Fernando and Deller (2021)[27] used behavioral data of both teachers and students to build a student's performance prediction model. Teachers' experience, teaching style, skill in IT were some of the few features included in the prediction model. A web-based prediction model was built in this study

3. RESEARCH METHODOLOGY

The current work entails Recurrent Neural Network along with the hybrid Firefly and Particle Swarm Optimization Algorithm. The data on the students for the study was collected 210 samples. In the proposed methodology, the RNN was employed to update the weight and biases in the model and the hybrid HFP was employed to optimize the feature selection process. Initially, the proposed model is trained with 80% of the dataset. Subsequently, the trained model is then tested with the remaining dataset. The following sub-stages are implemented in the python software and are explained below;

3.1 Preprocessing

The pre-processing was the primary stage in any machine learning process, where the data gets transformed. The collected dataset may have some missing data and they are filled with the mean of the respective attributes. The categorical features, which depicts student's details are labelled numerically. Then the data is normalized using Min-Max Normalization technique.

3.2 Feature selection

The collected dataset consists of many features like name, age, Gender, marks and percentages achieved by the student in 10th and semesters. However, for predicting the future academic performance the features involving the mark is substantiate and those are need to be selected. The feature selection process is carried out through hybridized firefly and particle swarm optimization technique.

3.3 Feature selection and optimized Prediction

The expected marks of the student performance in their academics is conceded with the RNN and HFP algorithm that are given below:

3.3.1 Selecting the features

The selection of supervised features is mostly focused on the problem of labelling, and the significance 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 labelling that provides the maximum accuracy of the model.

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 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.

$$D = \arg\max[J(S)] \tag{1}$$

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

Generally, rooted on the type of output, this method is divided into two, weighted ranking method and subset selection model [24]. 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

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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 method is commonly used to reduce the sum of squares of residuals if the regression coefficient is absolute.

3.3.2 Hybrid firefly and particle swarm algorithm

Yang, Xin-She [28] had proposed "Firefly" a Bio-Inspired algorithm, which was a metaheuristic in nature, imitating the behaviour pattern of the fireflies. By nature, the fireflies have a tendency to be attracted towards luminous substances. Initially, real fireflies illuminate in discrete forms, while the designed fireflies will be considered as always glowing. When relating the two fireflies' brightness, the fireflies' locations must be reflected. In the real time, when a firefly is examining for another, it can simply see so far. When the distant of another firefly is long, the less bright it will be for the first firefly due to the intensity of light decreasing under the inverse square law.

Particle Swarm Optimization (PSO) was firstly introduced by R.C. Eberhart and J. Kennedy in 1995 [29]. Particle swarm optimization is a nature-inspired algorithm which is based on the social behaviour of birds in the flock. PSO generates its performance after the flocking or swarming animal patterns. PSO has particles that generate its sample in the form of swarm. Every particle is basically moved from one point to another. This mutation is carried out in an effective manner; likewise, each particle is relocated from its preceding location to a fresh, better location.

In general, Firefly algorithm has high computational time, complexity and slow convergence. Therefore, the PSO is used to enhance the performance of the traditional firefly algorithm. Also, Fireflies had no memories of personal best position (pbest) and velocity (V) alike particles. When two algorithms are combined and hybridized, PSO performs the search globally and provides swift convergence. Additionally, Firefly performs the search locally, as it backs the fine-tuning in exploitation. The HFP algorithm is defined as follows,

$$w = w_i - \left(\frac{w_i - w_f}{iteration\max} \right) \times iteration \quad (2)$$

$$f(i,t) = \begin{Bmatrix} false, if\ fitness(particle_i\, t) > gbest^{t-1} \\ true, if\ fitness(particle_i\, t) < gbest^{t-1} \end{Bmatrix} \quad (3)$$

$$A_i(t+1) = A_i(t) + Y_0 e^{-\gamma r_{ij}^2}\left(A_i(t) - gbest^{t-1}\right) + a \in_i \quad (4)$$

$$V_i(t+1) = A_i(t+1) - A_{i\_temp} \quad (5)$$

3.3.3 Recurrent Neural Network

Basics: The RNN, the sub-class of neural networks, generated the long-range inherent correlation in the middle of data samples. Basic structure of RNN is shown in Figure 1. However the general NN without any information about temporal input data order, RNN solves the problem on incorporating the time built notion idea into it. Compared to further NN architectures, RNNs with hidden layer will update them after every time-step process of the input. This confirms the input sequence temporal structure as valuable. Network nodes get input from recent data point x (t) as well as hidden state values of hidden layer in the earlier state h (t−1). Hence, inputs at time t have influence on network outputs to arrive in the future with the help of recurrent connections. Standard RNN with input vector $v = (v_1, \ldots, v_T)$ measures hidden vector $h = (h_1, \ldots, h_T)$ and output vector $y = (y_1, \ldots, y_T)$ by iterating equations (6) and (7) over t = 1, … , T.

$$h(t) = Q(W_{(hx)} x^{(t)} + W_{(hh)} h^{(t-1)} + b_h) \quad (6)$$

$$y^{(t)} = \sigma(W_{(yh)} h^{(t)} + b_y) \quad (7)$$

Where: b_y and b_h as vectors of biases, $W_{(h,x)}$, $W_{(hh)}$ and $W_{(yh)}$ as weights matrices of input-hidden layer, hidden-output layer and recurrent connections separately. Q is an activation function.

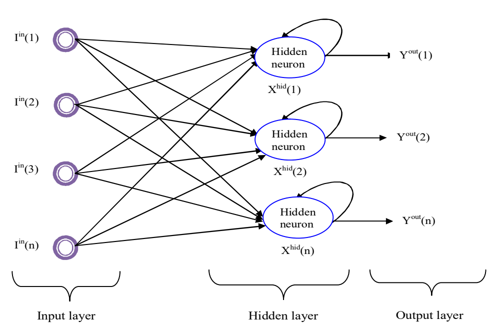

Figure 1: *Basic structure of Recurrent Neural Network*

Standard neural networks are instructed over numerous time steps using algorithm called backpropagation through time [30].

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Bi--LSTM-RNN network model is used, which includes input layer, output layer, 3 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.

$$I_l^t(t) = d_j^1(t-1) \tag{8}$$

$$I_m^t(t) = d_q^1(t-1) \tag{9}$$

Where I- input layer, d- dense layer l, m are order of context layer j, g are order of hidden layer.

At first hidden layer,

$$d_j^1(t) = f\left(\sum_i^1 V_{ij}^1 x_i(t)\right) + f\left(\sum_i^{con^1} u_{ij}^1 I_l^t(t)\right) \tag{10}$$

Where $f = \dfrac{1}{1+e^{-x}}$

The output layer is given as,

$$O_k(t) = f\sum_g^{D_2} W_{gk} d_g^2(t) \tag{11}$$

Where W_{gk} means the connection in the middle of second hidden layer and output layer.

3.3.4 RNN-HFP Predictor model

In the phase of training, the proposed model has two sub phases; The HFP algorithm initializes the values for weight, biases and its variables in vector form. The HFP algorithm selects the features which as more impact to predict the semester. Initially the velocity and the position of the particle is assigned. During the iteration the particles update their velocity and position by itself. After finding the velocity and position of the particle it will calculate the global best position. From the given gbest position it will move to the firefly algorithm. In order to find the best feature element, the predefined threshold value is set to 0.50. Based on the threshold value the feature will be accepted or rejected. After finding the feature which has more impact on the mark prediction will be given to the Bi--LSTM-RNN . The data was sent into the RNN that process the data through the dense layer and the output is given in the output layer. The total error in predicted value (MSE) was evaluated. The training process is constant and procedure continues until the convergence is met. After the training process is completed, the testing process is executed for appraising the performance of the trained prediction model. In this testing phase or prediction phase, 20 % of data from the dataset are given as input to the trained prediction model for predicting the performance of the students.

3.3.5 Algorithm: RNN-HFP algorithm

The step-by-step process of proposed prediction model is discussed in Table 1,

Table 1: Proposed RNN-HFP algorithm

Input: Student's previous years Mark **Output: predicted Next semester Mark**
(1). Start (2). Student's details and marks from previous semester is taken and stored in array of three dimension (N, W, F) Where, N is number of training dataset W is dataset length F is number of features in the dataset (3). Finding the features that have more impact on the upcoming semester mark prediction using HFP algorithm (4). Bi--LSTM-RNN is built which includes input layer, output layer, 3 hidden layers (including BiLSTM). This model is activated by sigmoid activation function and optimized using adam optimizer. (5). Assigning random weight and bias according to the dataset features (6). Train the constructed Bi—LSTM-RNN network on the dataset. (7). Use the output of the last layer's prediction of next number sequence. (8). Update the weight and bias based on MSE and set it for RNN (9). Repeat the above three steps until optimal solution is reached. (10). Obtain Prediction by providing test data as input to the network. (11). End.

4. RESULT AND DISCUSSION

In this section, results and discussion of Bi--LSTM-RNN-HFP based proposed prediction model is discussed and analyzed. The data are collected from the ITI institution in Bangalore. The sample consists of 210 data that are preprocessed and subjected to feature selection through Python Jupyter environment. The model was initially trained with 80% of data and tested with 20% of it. On Implementing Hybridized Firefly and PSO, the total numbers of features get reduced from 15 to 8 and are given in Table 2. Here, the feature selection process is implemented using Jupyter. Also, the proposed

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prediction model is executed using python software. The impact percentage greater than 50% is selected and is trained using the Bi--LSTM-RNN model to predict the semester mark.

Table 2: Results From HFP Algorithm

Features	% impact on Final Semester marks prediction
Sex	72.92368
Age	11.98001
Subject	28.59648
Medium of Instruction	0.833868
Month/year Appeared for 10th Exam	22.98286
Kannada	24.70796
Maths	76.20424
Science	48.12205
Social Science	57.42757
Total (425)	1.467815
Percentage	75.36456
Sem I	44.62953
per1	87.84088
Sem2	1.30197
per2	93.08649
Sem 3	87.22387
per3	90.7936

The proposed model was evaluated both at the testing and training for its accuracy over the given dataset. Initially 167 data is utilized to train proposed model and then 43 data are used for testing purpose. The percentage obtained in semester 1, 2, and 3 and the achieved 10th percentage were employed to predict the semester mark through the proposed Bi--LSTM-RNN model during the process of training. After the completion of training process, the percentage obtained in 10^{th} std, semester 1, 2 and 3 are provided to the predictor model and the model is trained. The loss is calculated using the mean squared error, which estimates the difference between predicted and true value. Figure 2 represents the variation between predicted semester 3 percentage and actual semester 3 percentage. As shown in the figure, the proposed prediction model has effectively predicted the percentage. Since the actual semester 3 percentage and predicted semester 3 percentage are almost converged. Therefore, RNN-HFP based proposed prediction has been better performed.

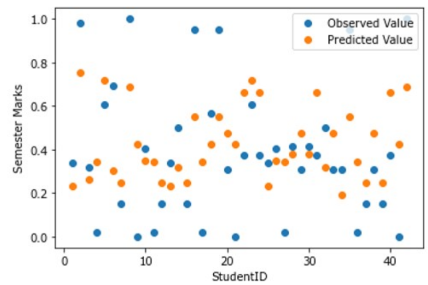

Figure 2: Predicted Semester Percentage Compared To Actual Semester Percentage. Blue: Observed Semester 3 Percentage And Orange: Predicted Semester 3 Percentage

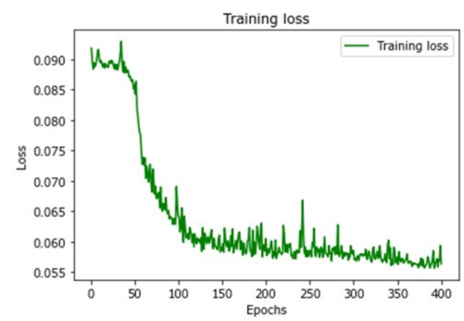

Figure 3: Loss Of The Proposed Model

The binary crossentropy loss of the proposed model was evaluated initially during the training phase and it showed the loss of about only 2%. Similarly, during the testing phase, the errors of the proposed model calculated using MSE was about 0.05, and using MAE (Mean absolute error) was about 0.13. The R square value of the predicted 3rd semester marks shows 61%. Figure 2 shows the loss of the proposed model under training phase.

5. SUMMARY

This research work developed a semester mark prediction for the ITI students in one of the Bangalore Institute. The hybridization of Firefly and particle swarm optimization algorithm produced a minimized error value using MSE 0.05. The previous study shows that the PSO algorithm used to find the feature selection run with the error rate of 0.098. Hence in our research we combined the

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Firefly and particle swarm optimization algorithms to minimize the error. The research must have concentrated to develop a modified RNN which helps to replace the adam optimizer. The future scope for the current work will underscore on anticipating the various attributes such as semester marks and behavioral data. Also, being the drop out student, the most impacted reason is because of unfortunate family situations.

Consequently the future work enhance the dropout detection models, by formulating multiple data.

6. CONCLUSION

In this paper, RNN-HFP algorithm is proposed to forecast 3rd semester marks of hearing impaired ITI students in Bangalore city. The academic scores obtained by the students in10th std and the previous semester marks are used for forecasting the final semester performance of the students. The RNN LSTM algorithm predicts the mark of the student through the optimized features with the HFP algorithm. The dataset is splitted in the ratio of 80:20 for training and testing the proposed model. The R square value achieved is 63%. The loss of the proposed model was evaluated initially during the training phase and it showed the MSE error of about only 0.05. Similarly during the testing phase the loss of the present model calculated using RMSE error was about 0.24. The prediction of 3rd semester marks also helped the institute to help the students to focus more with their academics. Hence the institute can maintain their admission level.

The future scope for the present work will emphasize on predicting the performance at earlier semesters. Additionally, being physically impaired the drop out cases from the education is more prevalent due to poor academic performance and family background. Hence the future work to predict the dropout chance of student earlier will benefit the student to endure the students to complete their education successfully and provide the necessary recommendation to guide them in their academics.

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