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A War Strategy based Deep Learning Algorithm for Students' Academic Performance Prediction in Education Systems

K.Sankara Narayanan[1], A.Kumaravel[2], S.Gopalakrishnan[3]

[1]Research Scholar, School of computing, Bharat Institute of Higher Education and Research, Chennai, Tamil Nadu, India.
[2]Professor, School of computing, Bharat Institute of Higher Education and Research, Chennai, Tamil Nadu, India.
[3]Associate Professor & Head, Department of Information Technology,
Hindustan Institute of Technology and Science, Padur, Chennai, Tamil Nadu 603103, India.
[1]ksankaranarayananphd@gmail.com
[2]drkumaravel@gmail.com
[3]drsgk85@gmailcom

Abstract : Researcher interest in education data mining has increased significantly in a variety of sectors. The recent research works use a variety of machine learning techniques to predict students' academic success in the educational sectors. They suffer from serious drawbacks like low forecast accuracy, high processing times, and overhead. Therefore, the proposed work aims to develop a new model for projecting students' academic progress. The main goal of this paper is to develop a smart and automated system for predicting the students' academic performance from the given students' data. For this purpose, a novel optimization and deep learning classification methodologies are implemented in this study. Here, the public UCI education training dataset is obtained to develop the prediction framework for forecasting students' academic achievement. The most correlated features from the preprocessed schooling dataset are chosen using the War Strategy Optimization (WStO) method to improve predicting performance. To effectively and reliably estimate the student performance rate with few wrong predictions, a classification method based on the Bi-directional Gated Recurrent Neural Network (Bi-GRNNet) is applied. The Arithmetic Operation Optimization Algorithm (AO2A) is used to correctly optimize the parameters of deep learning classifiers to guarantee minimal computing system complexity and quicker training. By using a complete performance evaluation study that takes into consideration a variety of various parameters, the output of the proposed WStO + Bi-GRNNet model is validated and analyzed. According to the findings, it is inferred that the proposed Bi-GRNNet integrated with WStO and AO2A technique performs well and provides an increased accuracy up to 99% while effectively predicting the students' academic achievements.

Keywords: Education Data mining, Students' Performance Prediction, Academics, War Strategy Optimization (WStO), Bi-directional Gated Recurrent Neural Network (Bi-GRNNet) Classification, and Arithmetic Operation Optimization Algorithm (AO2A).

K.Sankara Narayanan
Research Scholar, School of computing,
Bharat Institute of Higher Education and Research,
Chennai, Tamil Nadu, India.
ksankaranarayananphd@gmail.com

1. Introduction

In present days, the education data mining has gained a significant attention by many researchers [1, 2]. Based on the demands of the students, fresh opportunities and prospects for technologically improved learning systems have been developed and put into action by a wide range of study. For any kind of education to be successful, anticipating student performance is important [3, 4]. The most important indicator of educational achievement in any nation is student academic performance. In essence, aged, gender, teaching quality, and student learning all have an impact on students' academic progress. In education, there is a growing amount of interest in predicting student achievement in education [5, 6]. In a nutshell, educational achievement describes how well students accomplish both short-term and long-term targets for learning. Based on its rankings, an accredited institution needs to demonstrate a strong academic record. Therefore, if an institution has established credentials and academic successes, its ranking rises. From the perspective of the student, maintaining high academic performance [7, 8] boosts the chances of landing a job because outstanding learning is one of the main criteria taken into account by organizations. Moreover, the Information technology (IT) used for learning can help institutions produce better educational results. Typically, the Artificial intelligence (AI) [9-11] has several uses in the learning process, since the use of AI-based educational technologies has increased in order to garner attention while strengthening conventional teaching strategies and raising the bar for excellence. Additionally, these technology systems can offer information about pupil's grades, learning progress, internet activity, and attendance in class. Despite this, the large amounts of data and increasing level of detail make it difficult for educators to effectively adapt these strategies to their unique learning challenges. As a consequence, it grows increasingly challenging to evaluate pupils' performance precisely [12, 13]. In order to find variables that predict future student achievement, it is important to accurately analyze the data that has been gained. Educators must be able to anticipate and analyze students' performance in order

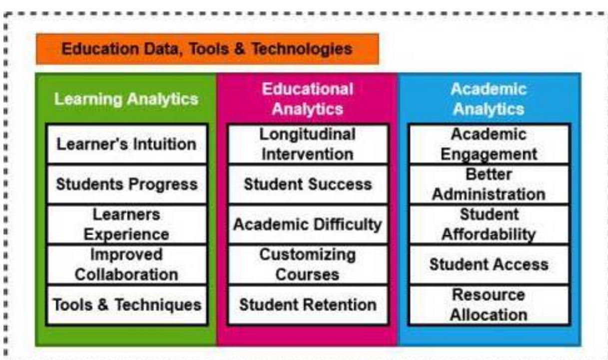

Fig. 1 : Education data analysis methods

to strengthen their academic achievement and identify their areas of weakness [14]. Similar to how administrators can enhance their operations, students can enhance their learning experiences. Fig 1 shows the typical education data analysis model.

Instructors can identify students who do poorly and participate at the start of the learning process to implement the appropriate interventions due to the early prediction of student performance. ML [15, 16] is a cutting-edge strategy having multiple uses that can forecast data. In educational data mining, ML approaches seek to simulate and identify significant hidden patterns and relevant data from educational settings. Additionally, ML techniques are used in the academic sector to represent a variety of student attributes as data points in big records [17-19]. By achieving a variety of objectives, such as identifying patterns, anticipating behavior, or discovering changes, such methods can be beneficial to a variety of professions. This enables educators to provide students with the most effective learning strategies for monitoring their progress. By using machine learning techniques, the students' performance can be forecasted based on information obtained from learning institutions and educational records. Modern methodologies and practical methods are crucial for transforming the learning environment. By assessing both the educational environment and machine learning approaches [20, 21], the education data mining model is essential for comprehending the learning environment for students. Numerous machine learning techniques are applied in the current studies to forecast students' academic achievement in the educational sectors. However, they have significant downsides such as low forecast accuracy, large system complexity, longer computation times, and high overhead. As a result, the suggested work intends to create a new model for projecting students' academic success. The following is a list of the main goals of this work:

- The public UCI education training dataset was gathered in order to create a new framework for predicting students' academic performance.
- To enhance the forecasting performance, the War Strategy Optimization (WStO) algorithm is used to select the most correlated features from the preprocessed education dataset.
- A classification method based on the Bi-directional Gated Recurrent Neural Network (Bi-

GRNNet) is used to accurately and efficiently estimate the performance rate of the students with minimal incorrect predictions.

- To ensure low computing system complexity and faster training, the Arithmetic Operation Optimization Algorithm (AO2A) is used to properly optimize the parameters of deep learning classifiers.

- The suggested WStO + Bi-GRNNet model's output is validated and examined utilizing a thorough performance evaluation study that takes into account a number of different parameters.

The remaining sections of this paper are divided into the following groups: For examining the various machine learning-based frameworks for predicting students' performance, a thorough assessment of the literature is offered in Section 2. In Section 3, the suggested WStO + Bi-GRNNet model is explained in detail. With the aid of the comparative findings in Section 4, the overall performance assessment is conducted. In Section 5, the paper summary, findings, and recommendations are presented.

2. Related Works

Sekeroglu, et al [22] applied a machine learning technique to predict the students' academic performance in the education institutions. Generally, education is one of the most necessary thing for an individual to lead a happy and good life, since it helps to improve the excellence of people all around the world. In order to increase the learning capability of students, there are various AI methods are developed for better teaching and learning. Xu, et al [23] intended to perform students' behavior analysis with the use of machine learning techniques for improving their academic performance and learning abilities. In this study, the most common and standard learning models such as DT, SVM, and NN have been used to predict the performance of students. Here, some of the internet usage features that are more correlated to the students' academics are extracted for enhancing the prediction rate. Masood, et al [24] conducted a systematic literature review to validate several data mining techniques for students performance prediction in education sectors. The authors of this study indicated that the quality assessment, data extraction and synthesis are the most essential models used to determine the learning performance of students. Moreover, the study results indicate that the standard DT and RF learning techniques provide an improved prediction performance results, when compared to the other learning strategies. Albreiki, et al [25] presented a comprehensive study to examine various types of machine learning methodologies for predicting students' academic performance in the learning environment. In this assessment, there are various data sources used for analyzing the students' performance in the educational environment. Moreover, the PISA dataset has been used in this survey for system validation, where the sample data is collected from several institutions of nine countries. Moreover, the early prediction supports to enhance the teaching effectiveness, students activity logs, and learning capacity. Alsariera, et al [26] conducted a performance assessment to validate several machine learning techniques to predict the students' academic performance in the education institutions.

Namoun, et al [27] conducted a systematic literature review to predict students' performance in academics. The main focus of this study to validate several learning-based approaches and prediction models for accurately determining the performance of students. Moreover, this study considered the statistical approaches, supervised & unsupervised learning models, and data mining techniques for performance forecasting. Waheed, et al [28] employed a deep Artificial Neural Network (ANN) technique with the set of hand-crafted features for analyzing the learning behavior of students in the education environment. The main purpose of this work is to formulate a new framework with the use of deep ANN for supporting the technology improved learning platform, where the students' academic performance prediction is mainly concentrated. In this framework, the effectiveness of the students' performance is predicted into the classes of distinction, with-drawn, and pass-fail. Francis and Babu [29] deployed a hybrid data mining approach for highly enhancing the students' prediction performance in the education sectors. Here, both clustering and classification techniques are used to obtain an increased prediction accuracy. Moreover, the standard classification approaches such as multi-class SVM, DT, NN, and NB are separately validated and experimented for choosing the most efficient technique for constructing the performance monitoring framework. Based on the statistical analysis of this framework, it is identified that the multi-class SVM provides an effective prediction performance. Hussain, et al [30] introduced a Technology Enhanced Learning (TEL) system for identifying the issues that the students facing in education. Moreover, the authors applied a set of machine learning algorithms including SVM and ANN to formulate the new framework called as, Digital Electronics Education and Design Suite (DEEDS) for improving the learning abilities of students in the education system. The results indicate that the ANN provides high accuracy with improved prediction results, when compared to the results of SVM. The key factor of this paper is to choose the most relevant and appropriate classification algorithm for determining the students' performance according to their session activities.

Kim, et al [31] designed a GridNet Model based on deep learning algorithm for predicting students' future performance in education. The LR is used as the base model for the suggested framework, where the Bag of Words (BoW) features are extracted for the learning process. The major drawbacks of this work are increased training and testing complexity with more time consumption. Balaji, et al [32] conducted a systematic review to analyze the impacts of using of machine learning techniques for students' academic performance prediction. Now a days, the machine learning techniques are considered as the most effective tool for used for improving the decision making performance of the suggested framework. In addition, the authors have conducted a quality assessment to examine the results of the suggested system. Hasim, et al [33] deployed a supervised learning technique to exactly forecast the students' final grades in the higher education systems. Moreover, the recent data mining techniques have been used in this study to determine the correlation among the user attributes with low system complexity.

According to the literature research, it is found that education data mining techniques [17, 34, 35] are being employed more frequently in the educational fields to improve students' academic achievement by anticipating their behavior activities. The majority of current research works struggle with intricate structures, lengthy processing times, and inaccurate performance prediction [36, 37]. As a result, the proposed research intends to put into practice of an innovative prediction model for anticipating students' academic success in the educational systems.

3. Proposed Methodology

The proposed prediction framework for predicting students' academic success in the education sectors is explained in detail in this section. The unique contribution of this work is the creation of a brand-new forecasting framework for the educational environment using cutting-edge data mining techniques. Fig. 1 depicts the proposed scheme's overall flow, which includes the following phases:

- Education training dataset collection
- Distance based data preprocessing

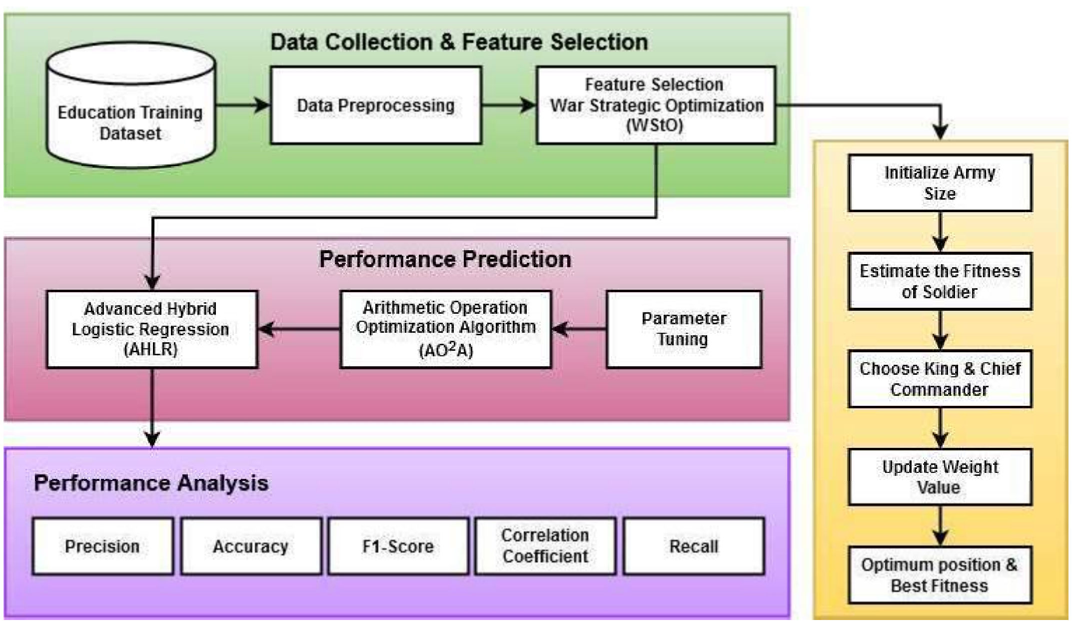

Fig. 2 : Work Flow Model Of The Proposed Students' Academic Performance Prediction System

- War Strategic Optimization (WStO) based feature selection
- Bi-directional Gated Recurrent Neural Network (Bi-GRNNet) based performance prediction
- Parameter tuning in classification using Arithmetic Operation Optimization Algorithm (AO2A)

The input education dataset used in this framework includes a number of different parameters, including name, study location, field, credit hours, family income, and education method [38-40]. The original training dataset frequently has certain missing fields of data or qualities, which might harm a prediction system's accuracy. In order to turn the raw dataset into the appropriate format, the distance-based preprocessing method is used in this work. It helps to normalize the information's properties. The most important characteristics are then selected from the preprocessed dataset using the WStO approach. Then, using the Bi-GRNNet mechanism, the performance of the pupils is predicted. Here, parameter modification is done to improve the overall forecasting performance. In order to tune the parameters of classifier, the AO2A technique is used in this work. Finally, the overall results and efficiency of the proposed students' performance prediction system is validated and tested by using a variety of parameters [41, 42]. In this work, the AO2A approach is employed to fine-tune the classifier's parameters. Finally, a number of characteristics are used to assess and test the overall outcomes and effectiveness of the suggested students' performance prediction method. When compared to the machine learning techniques, the deep learning techniques are more efficient and has the better ability to handle large dimensional datasets. Also, it effectively manage the missing data with high performance results. Due to an efficient decision making capability and prediction performance, the proposed work uses the deep learning algorithm to predict the students' academic performance. Since, the complexity of deep learning techniques are high, when comparing to the machine learning techniques. In order to solve this problem, we performed an AO2A based hyper parameter tuning, which simplifies the process of classification by accurately identifying the academic achievements of the students. By using the combination of AO2A – BiGRNNet models, the overall system efficiency and prediction accuracy are greatly improved in the proposed system.

In the field of education, there is an increasing interest in data mining. This can be seen from ongoing research that employs machine learning methods to anticipate students' academic advancement. However, these approaches often face issues such as low prediction precision, extended processing duration and substantial computing cost. To address these challenges, the research creates a new model for forecasting students' academic progress by designing an intelligent automation system using deep learning categorization techniques and optimization. For better forecasting, we utilize the UCI education training dataset to find out essential attributes for predicting academic performance. We then employ WStO technique in selecting these characteristics. Student performance is predicted precisely using a Bi-GRNNet, and parameters of deep learning classifier are fine-tuned by AO2A for ensuring minimal computational complexity and quicker training. Although the reasoning for selecting Bi-GRNNet is explained, the paper could give a more thorough explanation for the decision to choose this particular algorithm over others, like Transformer models, LSTM networks, or even more basic methods like Random Forests and Gradient Boosting Machines, which could potentially provide faster training and simpler interpretation.

A. War Strategic Optimization (WStO) based Feature Selection

The most pertinent characteristics from the preprocessed dataset are selected during this procedure using the cutting-edge WStO approach. Numerous feature selection strategies are used in the current studies to reduce dimensionality and optimise features. However, the majority of methods suffer from significant limitations such as prolonged searching times, poor performance, and slow processing convergence rates. As a result, the proposed work intends to create a new feature selection algorithm called WStO. In the proposed students' academic performance prediction system, the War Strategic Optimization (WStO) technique is mainly implemented to choose the optimum number of features from the preprocessed dataset with the use of best optimal solution. After getting the students dataset from the UCI repository, the attributes distance based preprocessing methodology is applied to clean the data by filtering the unwanted information and missing fields. The preprocessed dataset comprises some valid information or attributes, if we directly use the normalized dataset for classification without feature selection, the classifier's training and testing complexity can be increased. It also affects the accuracy and efficiency of the prediction results. Therefore, the WStO technique is applied before classification, which gives the best optimal solution to select the best features or attributes from the normalized dataset.

This method originated based on the tactical deployment of army units during battle. Each soldier moves dynamically in the direction of the ideal value in a combat plan that is portrayed as an optimization process. In this algorithm, the troops of one army strategically disperse themselves at random across the entire battlefield before invading the other army. The commander or army leader is the most formidable member of the army with the greatest offensive force. The King commands several of these troop heads. Travelling in two distinct chariots with flags on top, the King and the Commander Ride in tandem. The locations of the monarch and commander determine how the Soldiers' positions vary periodically. A soldier's rank will increase if he succeeds in increasing the offensive strength (fitness value). The soldier returns back to his original position if the new one is insufficient for combat. Army units move in any direction and take substantial steps to modify the positions they held at the start of the conflict. Depending on the circumstances on the battlefield, the King adjusts his plan on the go. As a result, a squad of troops rhythmically pounded the drums. According to the beat of the drums, the troops will alter their tactics and reposition themselves. In this algorithm, the input parameters such as army size, rank of soldier, and problem dimensionality are initialized, and the fitness function is computed for choosing the King and commander. Here, the King, the Army commander, and the soldiers are still extremely close to the target as the conflict draws to an end. It is mathematically represented by using the following model

$$P_i(h+1) = P_i(h) + 2 \times \sigma \times (C-K) + \beta \times (\omega_i K-P_i(h)) \quad (1)$$

Where, P_i (h+1) indicates the new position, P_i (h) denotes the previous position, C and K are the position of commander and king respectively, ω_i is the weight value, and β represents the random number. When the targeting force at the new position is lower than in the initial position, the soldier moves to the former location. It is mathematically represented in the following equation:

$$P_i (h+1) = (P_i (h+1))\times(R_x \geq R_y)+(P_i (h))\times(R_x<R_y) \quad (2)$$

According to the rank value, the new weight value is computed as shown in the following equation:

Where, δ is an exponential factor, r_i is the rank value, and Mx_itr represents the maximum number of iterations. In addition, the rank and weight values are updated according to the following equation:

$$P_i (h+1)=P_i (h)+2\times \sigma\times(K-P_\beta (h))+\beta\times\omega_i\times(C-P_i(h)) \quad (4)$$

Consequently, the weak soldier is replaced with the random soldier as shown in the following model:

$$P_\omega(h+1)=Low_b+\beta\times(Up_b-Low_b) \quad (5)$$

The second strategy involves moving the weak soldier in a fighting zone closer to the army's median, as shown in the following equation:

$$P_\omega (h+1) = -(1-\beta x)\times(P_\omega (h)-median(P))+K \quad (6)$$

This algorithm is utilized to select the most pertinent aspects from the provided educational data, which helps to improve the overall accuracy of predicting students' performance.

B. Bi-directional Gated Recurrent Neural Network (Bi-GRNNet) Classification

The academic achievement of the students is accurately predicted using a Bi-GRNNet process after selecting the most closely associated factors from the education data. Among other classification approaches, the main reason of using this technique is, it has the better ability to handle the high dimensional data with increased accuracy. In addition, some other major reasons for choosing this technique are easy to implement, effective data training, and better system performance. This technique is an advanced version of GRN, which is treated as the best alternative for LSTM model. Generally, the GRN technique integrates both the input and forget gate into the update gate with the use of hidden state information. The proposed Bi-GRNNet model is formulated by stacking two distinct GRU layers at the top, in which one is for forward direction, and other is for backward operation. During forward operation, the hidden states are computed in the form of $(\vec{h}^1),(\vec{h}^2),(\vec{h}^3)\ldots(\vec{h}^m)$, and is reversed in the backward direction that is represented in the form of $(\overleftarrow{h}^1),(\overleftarrow{h}^2),(\overleftarrow{h}^3)\ldots(\overleftarrow{h}^m)$, where m indicates the time step. Moreover, the information access is enhanced with the backward flow of GRU, which processes the given data at the opposite direction. Here, the hidden layer functions are computed as represented in the following models:

$$(\overleftarrow{r^m}) = \varphi\,((\overleftarrow{\omega^r})\,(\overleftarrow{h^{(m+1)}}) + (\overleftarrow{A_r})\,(\overleftarrow{Sm}) + (\overleftarrow{b^r})) \quad (7)$$

Where, the symbol ← indicates the backward direction, $(\overleftarrow{r^m})$ is the reset gate, $(\overleftarrow{S^m})$ denotes the input gate, $(\overleftarrow{b^m})$ is the bias value, $(\overleftarrow{A^m})$ indicates the input weight matrix, $(\overleftarrow{h^{(m+1)}})$ is the hidden state, and $(\overleftarrow{\omega^r})$ denotes the recurrent weight matrix. Consequently, the candidate cell $(\overleftarrow{c^m})$ is computed based on the following model:

$$(\overleftarrow{c^m}) = \tanh((\overleftarrow{\omega^c})\,((\overleftarrow{r^m})\otimes(\overleftarrow{h^{(m+1)}})) + (\overleftarrow{A^c})(\overleftarrow{S^m})+(\overleftarrow{b^c})) \quad (8)$$

Then, the update gate is computed as shown in the following equation:

$$(\overleftarrow{u^m}) = \varphi((\overleftarrow{\omega^u})\,(\overleftarrow{h^{(m+1)}}) + (\overleftarrow{A^u})\,(\overleftarrow{S^m}) + (\overleftarrow{b^u})) \quad (9)$$

Finally, the hidden state updation is performed as shown in the following equation:

$$(\overleftarrow{h^m}) = (1-(\overleftarrow{u^m})) \otimes (\overleftarrow{h^{(m+1)}}) + (\overleftarrow{u^m})\otimes(\overleftarrow{c^m}) \quad (10)$$

Where, $(\overleftarrow{A^r})$, $(\overleftarrow{A^c})$, $(\overleftarrow{A^u})$ are the input weight matrices that are correlated with the input data $(\overleftarrow{S^m})$, and $(\overleftarrow{\omega^r})$, $(\overleftarrow{\omega^c})$, $(\overleftarrow{\omega^u})$ are the recurrent weight matrices that are correlated with the hidden state $(\overleftarrow{h^{(m+1)}})$, and $(\overleftarrow{b^r})$, $(\overleftarrow{b^c})$, $(\overleftarrow{b^u})$ are the bias values correlated with the backward operation. Finally, the output state of hidden information is represented in the following form:

$$h^m = (\overleftarrow{h^m}) \oplus (\overleftarrow{h^m}) \quad (11)$$

Where, ⊕ represents the element-wise operation. The proposed system for predicting students' academic achievement employs this algorithm to carry out the better prediction process. In order to greatly improve the performance of the Bi-GRNNet model, the optimal parameter tuning is performed with the use of AO2A.

C. Arithmetic Operation Optimization Algorithm (AO2A)

The primary goal of applying this AO2A in this work is to optimally adjust the parameters of the suggested deep learning mechanism. In the proposed work, the Bi-GRNNet model is mainly used to accurately predict the students' academic performance from the given data. When comparing to the other deep learning techniques, the main reasons behind the usage of Bi-GRNNet are lower computational complexity, requires less computational time to train and test the input samples, and higher efficiency. Moreover, it has the ability to effectively handle both the low and high dimensional data with less system burden and high prediction performance. In addition, the AO2A technique is implemented to optimally compute the weight values according to the best optimum solution. It helps to increase the overall detection performance and efficiency of the prediction. The parameter tweaking typically aids in enhancing classification accuracy. Due to their primary issues of high computational complexity and time consumption, most categorization algorithms are ineffective. As a result, the proposed study uses AO2A to fine-tune the classifier's parameters in order to reduce the computational load on the classifier.

It is a meta-heuristics model that makes use of four fundamental arithmetic operations such as addition,

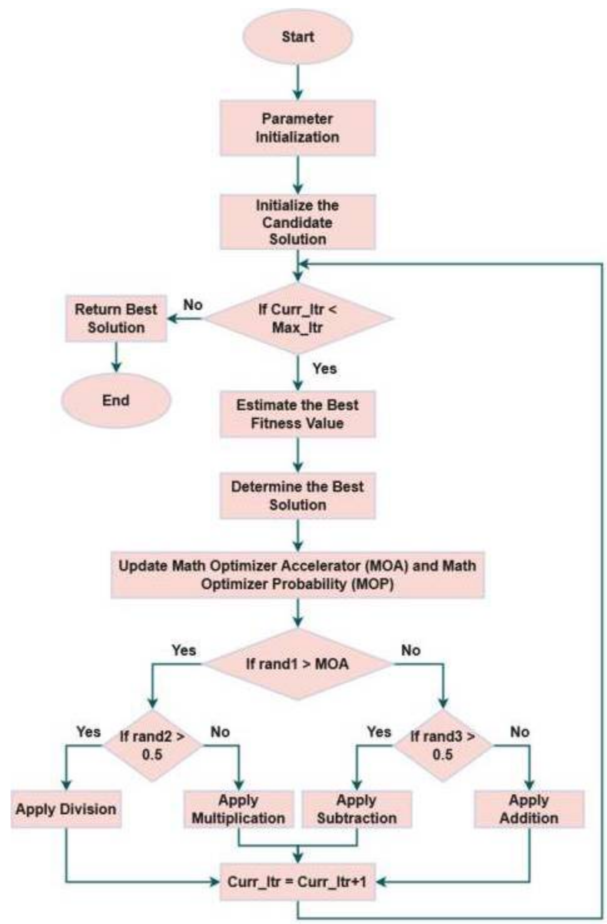

Fig. 3 : Flow of AO2A

subtraction, multiplication and division. Moreover, it is modelled mathematically and put into practice to carry out the optimization processes in a variety of search areas. This algorithm comprises the major phases of exploration and exploitation, where the local solutions are avoided with an extensive use of searching space. At the beginning, the set of candidate solutions are initialized for randomly generating the matrix. Then, the math optimizer accelerator function is computed in the searching space with the minimum and maximum of accelerated functions. After that, the exploration operation is carried out to obtain the better solution with the multiplication and division strategies. Consequently, the high dense-results are obtained during exploitation with the addition and subtraction operators. The overall flow of the AO2A is shown in Fig 3

The interest in education data mining for research purpose has grown considerably among different fields. Recent studies are using various machine learning methods to predict students' academic achievements. But, many of these approaches have serious limitations like low prediction accuracy, long processing times and require significant computational resources. Solving these problems, the paper suggests a fresh model to predict academic progress of students. The main purpose of this study is to create a smart and automated system for forecasting students' academic performance. To do this, we use new optimization and deep learning classification methods. We make use of the given public UCI education training dataset in order to design a prediction framework which can forecast students' academic achievements. The chosen characteristics from the prepared dataset are picked with the help of War Strategy Optimization (WStO) technique, which boosts prediction results. A good way to estimate student performance is by using a classification method that depends on Bi-directional Gated Recurrent Neural Network (Bi-GRNNet). Also, we use an Arithmetic Operation Optimization Algorithm (AO2A) for making better these parameters of deep learning classifiers. This helps us to maintain low computational complexity and faster training. A detailed performance evaluation is done, using different parameters to confirm and study the output of the WStO + Bi-GRNNet model. The results show that the suggested Bi-GRNNet mixed with WStO and AO2A methods works very good, giving correct predictions for students' academic successes up to 99%.

4. Results and Discussion

The performance results of the proposed WStO + Bi-GRNNet model is validated and compared by using the public UCI education dataset [43]. The public students' dataset available from the UCI repository used in this study comprises 33 distinct attributes. By using the proposed WStO technique, the total number of features required for the students' academic performance prediction is reduced to 17, which are used for the classifier's training and testing operations. This kind of feature reduction helps to minimize the overall dimensionality of dataset with better prediction results. The dataset details are provided in the following Table 2 and its attribute information is represented in Fig 4. The different types of parameters used to evaluate the results of the proposed framework are computed based on the followings:

$$\text{Accuracy} = \frac{\text{Tp+Tn}}{\text{Tp+Tn+Fp+Fn}} \quad (12)$$

$$\text{Precision} = \frac{\text{Tp}}{\text{Tp+Fp}} \quad (13)$$

$$\text{Recall} = \frac{\text{Tp}}{\text{Tp+F}} \quad (14)$$

$$\text{F1} - \text{score} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision+Re}} \quad (15)$$

$$\text{MCC} = \frac{\text{Tp}*\text{Tn}-\text{Fp}*\text{Fn}}{\sqrt{(\text{Tp+Fp})(\text{Tp+Fn})(\text{Tn+F}\ \ )(\text{Tn+Fn})}} \quad (16)$$

$$\text{Kappa} = \frac{x_o - x_e}{1 - x_e} \quad (17)$$

Where, Tp – true positives, Tn – true negatives, Fp – false positives, Fn – false negatives, x_o – observed agreements, and x_e – expected agreements.

Table 1 :
Dataset description

Parameters	Descriptions
Type	Multi-variate
Total no of instances	649
Domain	Social
Attribute type	Integer
Total no of attributes	33
No of web hits	134136
No of classes	3

Fig 5 and Table 3 validates and compares the overall performance and prediction results of the proposed WStO + Bi-GRNNet model using the entire UCI dataset. Similarly, the performance results are

1	Education Institution	12	Travel time
2	Gender	13	Study Time
3	Age	14	No of failures
4	Address	15	Extra curricular activities
5	Family Size	16	Higher education
6	Father's education	17	Family education support
7	Mother's education	18	Family relationship
8	Father's job	19	Current health status
9	Mother's job	20	No of absences
10	Reason to choose the institution	21	Work day alcohol consumption
11	Student's guardian	22	Weekend alcohol consumption

Fig. 4 : Dataset attribute information

validated for the training (80%) and testing (20%) datasets separately as shown in Fig 6 and Fig 7 respectively, and its tabular values are represented in Table 4 and Table 5. For this analysis, three different classes such as pass, fail and average are considered for predicting students' performance in academics. From the results, it is inferred that the proposed WStO + Bi-GRNNet technique provides an increased accuracy (99%), precision (98.6%), recall (98.7%), f1-score (98.6%), MCC (98.6%), and kappa (98.4%) values by accurately identifying the classes.

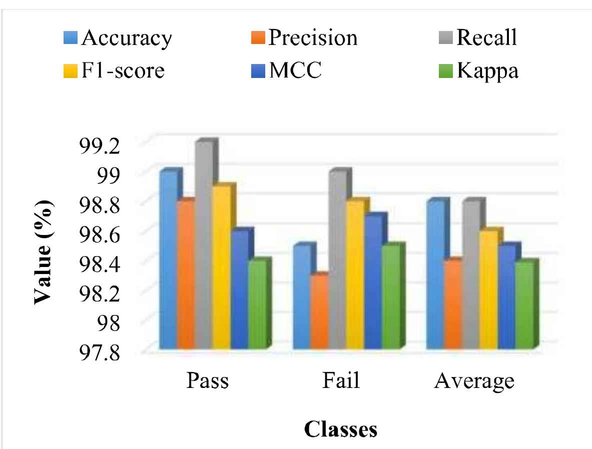

Fig. 5 : Performance analysis for the overall dataset

Table 2 :
Overall performance analysis

Predicted classes	Accuracy	Precision	Recall	F1-score	MCC	Kappa
Pass	99	98.8	99.2	98.9	98.6	98.4
Fail	98.5	98.3	99	98.8	98.7	98.5
Average	98.8	98.4	98.8	98.6	98.5	98.39

Table 3 :
Performance analysis using training dataset

Classes	Accuracy	Precision	Recall	F1-score	MCC	Kappa
Pass	99.2	99	99.5	99.4	98.9	99.18
Fail	99.3	98.2	99.2	99	99.1	99.27
Average	99	99.1	99	99.26	99.29	99.16

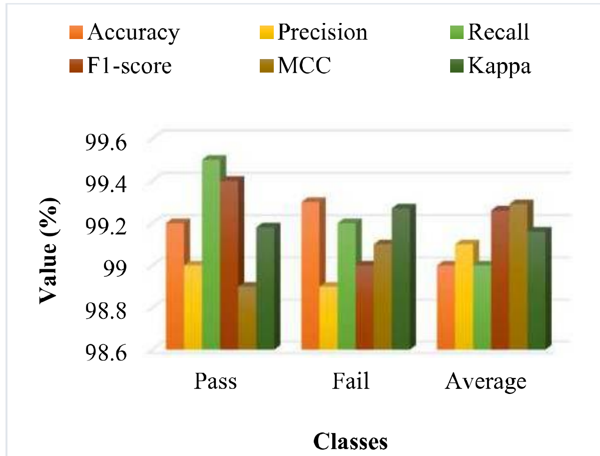

Fig. 6 : Performance analysis for the training dataset (80%)

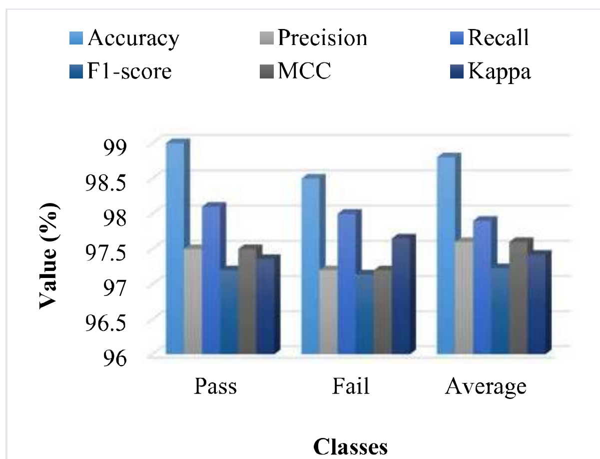

Fig. 7: Performance analysis for the testing dataset (20%)

Table 4 :
Performance analysis using testing dataset

Classes	Accuracy	Precision	Recall	F1-score	MCC	Kappa
Pass	99	97.5	98.1	97.2	97.5	97.36
Fail	98.5	97.2	98	97.14	97.2	97.65
Average	98.8	97.6	97.9	97.23	97.6	97.42

By using the UCI dataset, Figs. 7 and 8 validate and contrast the performance results of the existing and suggested prediction techniques [44, 45]. According on the observed outcomes, the suggested WStO + Bi-GRNNet model performs significantly better than previous machine learning-based classification approaches.

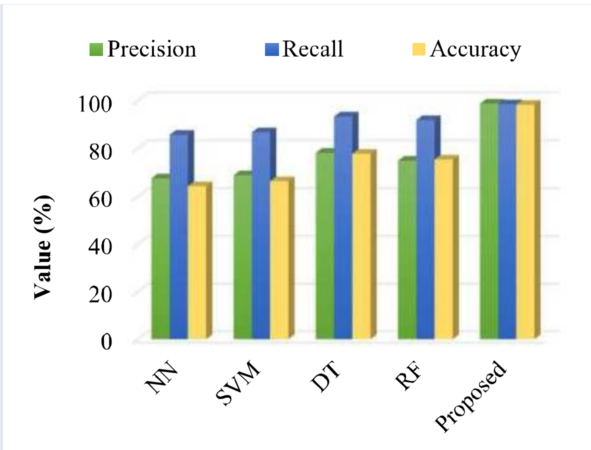

Fig 8: Comparative analysis

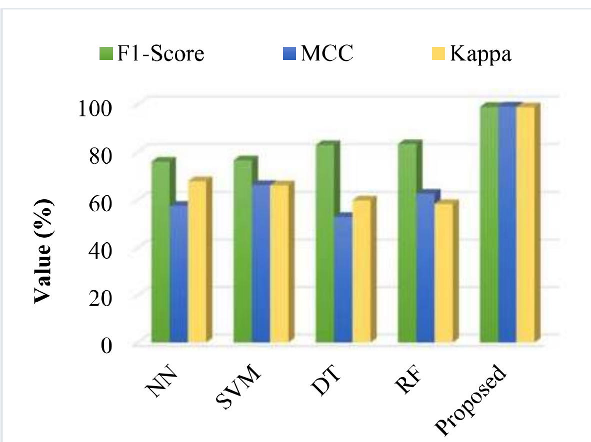

Fig. 9. :Comparative analysis based on similarity coefficients

The prediction performance results of the proposed Bi-GRNNet classifier in this work are significantly improved with the addition of WStO and AO2A approaches. Because low false predictions and faster classification training are made possible by features with lower dimensionality. As a result, the best parameter tuning aids in helping people solve their difficulties accurately. The suggested prediction model thus outperforms the traditional categorization strategies with much better forecasting outcomes.

The demand for education data mining is growing in many areas. In recent studies, a range of machine learning methods are used to forecast students' performance. But these techniques can often be limited by problems like low prediction accuracy, long processing times and large computational requirements. For solving these problems, the paper suggests a new model to predict students' academic advancement. The main aim of this study is to create a unique and automatic system for forecasting students' academic performance by using the student data provided. For this purpose, we make use of new optimization and deep learning classification methods. We focus on the public UCI education training dataset as our base to create a prediction framework for anticipating students' academic achievements.

Highlighted features come from the preprocessed dataset, chosen by the War Strategy Optimization (WStO) technique. This method improves how well we can predict results. To estimate student performance precisely and with as few errors as possible, we use a classification method based on Bi-directional Gated Recurrent Neural Network (Bi-GRNNet). We also apply the Arithmetic Operation Optimization Algorithm (AO2A) to optimize parameters of deep learning classifiers. With this, we aim for least computational complexity and faster training. A different important issue is the generalizability of our model to various educational situations. We train and confirm our results on the UCI education training dataset, but this might not include all possible variations in student data from different places, teaching systems or demographic groups. As a result, when we use the model with fresh data that has not been seen before and is very different from what was used for training it could lose its effectiveness. A thorough performance evaluation is carried out, considering various parameters to examine the outcomes of the suggested WStO + Bi-GRNNet model. The results illustrate that the proposed Bi-GRNNet with WStO and AO2A methods functions significantly well, demonstrating an accuracy score nearing almost 99% for predicting students' academic achievement.

Furthermore, the usefulness of the framework in large-scale educational settings may be limited due to the lack of a thorough investigation of the computational complexity and scalability of the suggested methodologies. It is still unclear how the model would function in situations involving larger datasets and more complicated learning settings in the absence of such research. Subsequent investigations ought to concentrate on mitigating these constraints by refining the model's comprehensibility, putting it to the test on a variety of datasets to gauge its applicability, and carrying out exhaustive analyses of computing complexity and scalability. The suggested approach can be put in a better position to be used successfully in larger educational environments by solving these issues.

Conclusion

This study creates a novel framework for forecasting students' academic success using the WStO + Bi-GRNNet model. Here, the suggested system has been implemented using a publicly accessible UCI education dataset. The education dataset used to build this framework includes a wide range of parameters, such as name, study location, field, credit hours, family income, and educational mode. The original training dataset often contains missing data or attributes, which could reduce the accuracy of the prediction system. The distance-based preprocessing method is used in this work to transform the raw dataset into the required format. As a result, the information's properties are standardized. The most relevant features from the preprocessed dataset are then selected using the WStO method. The performance of the pupils is then predicted using the Bi-GRNNet method. In this case, parameter adjustment is implemented to enhance overall prediction performance. The AO2A method is used in this work to adjust the classifier's parameters. The final step is to evaluate and test the overall results and effectiveness of the proposed strategy for predicting students' performance. The final stage is to assess the overall outcomes and effectiveness of the proposed technique for forecasting student achievement. The findings suggest that by correctly classifying the data, the suggested WStO + Bi-GRNNet technique offers higher accuracy (99%), precision (98.6%), recall (98.7%), f1-score (98.6%), MCC (98.6%), and kappa (98.4%) values.

In the future, the presented work can be expanded by incorporating fresh data imputation and classification methods to create a framework for performance prediction. Future research could focus on the following areas: (1) more learning diagnosis models can be introduced for learning improvement and analysis; (2) the learning activities can be monitored and evaluated over time, and dynamically track developments in learners' knowledge proficiency. The model's input data can be enhanced with learner behavior information to produce more precise test results.

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