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# Blockchain Framework for Learner Performance Prediction using Life-Brain Storm-based Light GBM Coupled Neural Network

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E-learning is one of the dominant applications of digital techniques in the educational platform. Tutors can effectively tailor their instruction to each student by using the automatic identification of the student's learning styles. Nowadays Deep learning techniques provide the preferable predictive model in the e-learning platform. Hence, this research article provides the prediction of the learner's performance by using the Life-Brain Storm (Life-BS) based LightGBM coupled Neural Network (NN). A significant part of the research lies in the tuning of the hyper-parameters using the proposed Brain rule selection algorithm, which boosts the accuracy of the classifier. Furthermore, by lowering the dimensionality of the data, the feature extraction approach is developed in this study to reduce the computational complexity of the prediction framework. The suggested Life-BS-based LightGBM coupled NN model is shown to be effective by the experimental assessment, which yielded the lowest RMSE as well as the MSE for courses 1, 2, and 3, respectively. In addition, the evaluation metrics such as MAE and Kappa scores achieve better results for course-1, course-2, and course-3 respectively. Use of blockchain, including kappa score also in performance metrics along with Life-Brain Storm based LightGBM coupled Neural Network proposed learner performance prediction model are the keypoints of the presented work.

**Keywords:** Blockchain, Deep-learning, e-khool LMS, E-learning, Performance prediction model

## Introduction

There is a tremendous advancement in the field of higher education due to the contribution and support of Information and Communication Technology (ICT). The quality of distance education is enhanced through the distance learning provided by the advancement in ICT.[1–5] Most educational institutions and academic organizations are now able to minimize their provision cost, which in turn enhances the income of the organization. Further, the online learning concept that renders greater service to the educational field is the significant innovation of ICT. Online learning enables the students to learn the concepts without the physical presence of the tutor. This mode of learning without the tutor emerged from the ideas of television courses of the 1980s. The gradual advancement in the technique provides a new online learning technique known as electronic, virtual, or distance learning.[6–10] The flexibility of the students is significantly increased by the online learning platform, which in turn enhances the learning experience and academic performance.[11] The reduction in the topographic gaps, inexpensive learning, and the accessibility of the course material are the main advantages of the e-learning system. Nowadays, e-learning systems and their applications are being promoted by governments everywhere, especially in higher education. Therefore, in order to raise the caliber of the educational process, both instructors and students must embrace the e-learning system. The importance of e-learning systems in developing nations is emphasized by recent empirical assessments.

The usage of blockchain innovation in the educational system is similar to the research domain

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as a couple of works have been done in that space and consequently, a possible advancement in e-learning is commonly online instruction and virtual learning. blockchain innovation has shown to be more effective in getting instructive information than the other techniques, subsequently; the utilization has supported carrying out Bring Your Gadget (BYOD) in schools.[12] Blockchain innovation can be utilized to store instructive documents in a reliable decentralized framework, offering dependable computerized certificates, perceived training assets imparting to keen agreements, and secure scholarly materials utilizing information encryption. Different advantages of utilizing blockchain are reliability, data integrity, and immutability. The utilization of blockchain innovation in educational establishments has many advantages, for example, protects individual assets, which is a system against legal action, guarantees responsibility[13], works on the image and prominence of scholastic associations, guarantees that scholarly information is secured against illegitimate modification, for example, certificate forgery, certificate manipulating and falsification, accelerating the preparing of college scholastic records[14], transferring the academic records between the educational institution and finally it guarantee straightforward graduation necessities that cannot be altered without legitimate approval.[15] This is a part of the security and legitimate confirmation of historical data of students.

The traditional methodology comprises recognizing learning styles through the opinion poll that students are approached to finish up. However, this methodology presents a few constraints that are identified with students' lack of involvement in finishing a survey and absence of consciousness of their learning precedence. Thus, the programmed approaches were presented to overcome the restrictions of the ordinary methodology.[16] These programmed approaches comprise gathering data from the students' collaboration with the instructive framework. Afterward, Web Utilization Mining (WUM) is used to describe and initialize this acquired behavior, which aids in identifying a student's needs within the e-learning platform. Furthermore, a programmed technique can adapt as students' learning characteristics vary over time. Additionally, the programmed technique can be more accurate and less prone to error by using real data to identify students' learning styles. To address data gathered from instructional frameworks, a few studies have been established by taking into account various learning style models and unique AI characterization techniques. As a result, a vast array of techniques for determining learning styles have developed, including Bayesian network methods, Decision Trees (DTs) processes, and Neural Networks (NNs) procedures. Although various arrangement processes provide remarkable results, each method performs differently. This is due to differences between characteristics and factors about the data acquired from the educational frameworks. Furthermore, a few robustness-identified restrictions are present in these strategies.[17,3]

#### Literature Survey

The mixed technique approach using multiple-linear regression, social network analysis and Slavko Rakic *et al.*[1] reported K-means clustering by Both the teachers and the evaluators of the online courses saw value in the blended methods. This mixed-method approach's primary drawback is that it only takes into account the data set from the two courses. The adaptive sparse self-attention network was introduced by Xizhe Wang *et al.*[2] to forecast the performance of the learner. The primary benefit is that it offers more accurate prediction outcomes in addition to useful details about formative evaluation and tailored feedback for online learners. The primary disadvantage is that an excessively long input sequence drastically lowers the model's efficiency. The fuzzy C Means (FCM) algorithm was introduced by Ibtissam Azzi *et al.*[3] as a reliable method for analyzing learner performance. The method is strong because it can determine learning preferences for any number of courses that are taken into consideration throughout the identification phase. But this system's regulations must be changed regularly. An enhanced version of the Technology Acceptance Model was proposed by Nazir Ullah *et al.*[4] to assess the achievement of learners. The enlarged model provides a blockchain adoption model that could help policymakers create an intelligent learning environment for educational institutions in developing nations. The integration of blockchain technology with other technologies was not assessed using this method in terms of security and privacy. ANN was used by Aydoğdu and Şeyhmus[5] to estimate learner performance. The system can function effectively even with limited understanding. To improve the system's accuracy, the effects of varying neuron count in a single hidden layer in the artificial layer must be taken advantage of. SVM and LR were employed by Xizhe Wang *et al.*[6] to analyze the performance of the learners. For predicting pupils' future performance, the sequential minimal optimization approach of the support vector machine method will perform better. Nevertheless, the SVM will perform worse if there are more characteristics per data point than there are training data samples. A technique based on machine learning was presented by Ostapowicz and Bukowski[7]. Sensitivity analysis revealed that the suggested model is not overly sensitive to specific explanatory factors. This approach has to be improved further as it is only used in its current version. Liu *et al.*[8] assessed the learners' performance using video and LMS predictors. With this approach, an advanced prediction effect is obtained. The primary problem is the inequality in the data, which must be reduced by improving minority samples.

#### Challenges

In the real-time application, the Gravity Search Back Propagation Neural Network (GSBPNN) method was used to anticipate the students' preferred learning modes. However, the method is only meant to locate one course at a time.[3]

Using a neural network and fuzzy logic integration,[18] trains its model on several learning platform types. Nevertheless, the results are limited to classifying the three dimensions—input, perception, and comprehension.

The approach discussed here in Reference[19] uses a model to determine the risk that remote learning platform users face, and those who are identified as such are referred to the module team for assistance. However, the system does not focus on the important characteristics of the pupils. It covers all feature sets as a result.

The methods proposed in reference[20] predict the student's performance only using their scores without considering the socioeconomic data. However, there are only a few studies have been established to predict the performance of the students using the latent variables.[5]

The traditional classification algorithm discussed in reference[21] such as Bayesian suffers from performance degradation due to the loss of accuracy, when the input is fed in a continuous range.

The main aim of the research is to develop an efficient algorithm to predict the performance of students based on blockchain technology in the e-learning platform. To initiate the process in the blockchain network, the e-khool data[22], which contains information, such as Log file, subject ID, Topic ID, exam score, profile, exam score, study nature, chapters covered, and material type is utilized. From the datasets, the features, such as entropy-based features and statistical-based features are extracted. The extracted features are fed to the neural network (NN)[23] based prediction model, in which the training is executed with the aid of the proposed Brain rule selection algorithm. The algorithm integrates both characteristic features of Life choice optimization[24] and the Brain storm optimization.[25] Thus, a trained model is obtained through the proposed Life-BS optimization using the e-khool data. The obtained raw data will undergo feature extraction and be evaluated using the suggested approach to forecast the student's performance, once the test data is fed to the trained model. The efficacy of the suggested performance prediction model is demonstrated through an analysis of the techniques using performance measures including specificity, sensitivity, and accuracy and has been implemented in MATLAB. The proposed approach's performance is compared with that of other State-of-the-Art methods.

**Proposed Life-BS Optimization Algorithm**: The proposed Life-BS algorithm is developed by integrating the decision-making and problem-solving analytical skills of human beings.

**Proposed Life-BS Optimization Algorithm for Weight Optimization in the Classifier:** The proposed Life-BS algorithm would render an effective weight set for enhancing the accuracy of the NARX classifier

#### Application of Block-chain and Artificial Intelligence in Learner Performance Prediction

The digitalized education system namely, the Learning Management System (LMS) permits the online teaching interaction between the learners and the educators, where the educators share the educational contents for the learners and track the performance of the learners in the online platform. Thus, LMS is a digitalized platform that insists the collaboration and communication between educators and learners without any time and location constraints. LMS renders an easy teaching and learning experience and insists on the need for predicting the performance of the learner through the proper tracking of the learner activities in the LMS for which blockchain technology plays a major role through recording the learner transactions in chronological order. Moreover, the learner indicators gain significance in the learner prediction as without these indicators, the prediction becomes complicated and directly affects the prediction performance. Therefore, the learner indicators, like log files, learner ID, and so on are referred in this research. In addition to the learner indicators, feature extraction is employed for representing the confined features that explain the influential characteristics of the learner. In-depth modules of the prediction model are depicted in Fig. 1. Initially, the attributes are obtained from the e-Khool data, which is mathematically represented as

$$eD = \{A_i\}; (1 \le i \le N) \quad \dots (1)$$

where, $N$ refers to the total attributes in the dataset and $A_i$ is the $i^{th}$ attributes obtained from the database.

**Read the Learner Indicators:**

The learner indicators represent the learner profiles and learning situation, which are grouped under three different levels of indicators, such as behavioral, social, or cognitive indicators. Among the different indicator levels, the cognitive indicator is inferred in this research, where the indicators correspond to the various states that constitute the knowledge levels of the learner, which include the learning objectives, learning styles, activities engaged in the LMS, and so on. The discussion on the cognitive indicator-based learner indicator is detailed below.

***Log File:*** The log file of the learner holds the log-in time, the total time spent on a course, page traversing time, log-out time, and time for covering/learning the subjects.

***Subject ID:*** The subject ID represents the unique roll number for the lesson and the subject details of the learner.

***Topic Id:*** The topics are categorized under unique identities, which explain the sub-topics covered by a subject.

***Exam Score:*** The details regarding the topic assessment questions in the form of the model tests are available and the score for the learner is mentioned under the exam score.

***Profile:*** The identity of the learner with his/her name, gender, geographical location, highest education, undertaking the course, data of enrolment into a course/program, and topics of interest are detailed under the profile of the learner.

***Study Nature:*** The interest of the learner in undertaking a course for which the nature of

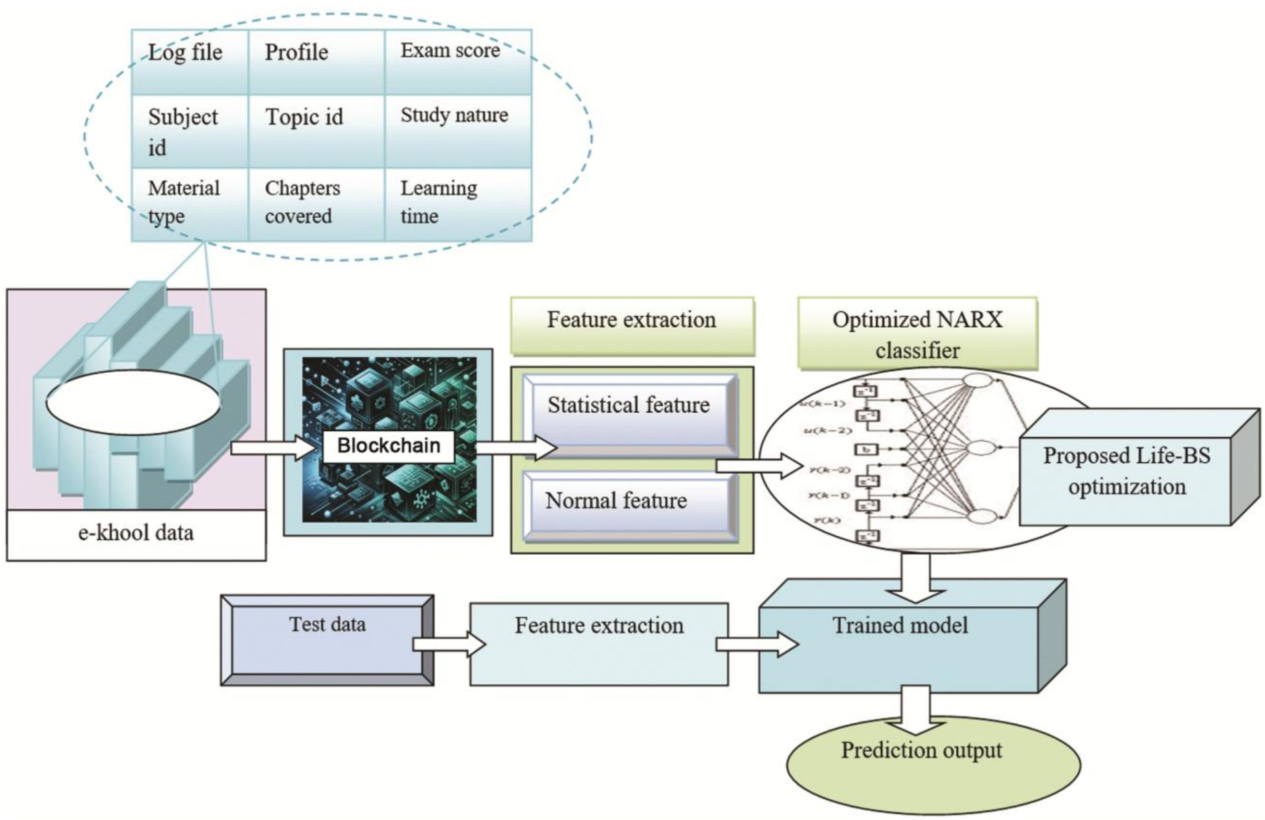



Fig. 1 — Block diagram of proposed prediction module

study includes the interested learning time, learning type (PDF, written notes, video/audio lectures), time spent by the learner on a normal day versus examination day/day-before the exams, and frequency of learning are discussed under the nature of the study.

***Chapters Covered:*** The grasping speed of the learner, understanding of the learner using the available sources from the educator, the total chapters updated in LMS, and the covered chapters with the coverage time are listed under this indicator.

***Material Type:*** The preferred study type of the learner among the available study materials is covered by this indicator.

***Learning Time:*** The duration to learn a chapter is covered by this indicator.

The learner indicators are acquired from the e-khool data[26,27], which is the user-friendly online LMS, and nowadays, e-khool is one of the attractive platforms among most of the learners as pandemic outbreak situations insist on e-learning. Attributes in Dataset has been depicted through Table 1, 2, 3 also

Table 1 — Attributes in the Dataset (Some Samples Taken from Dataset)

| | | | | | | |
|---|---|---|---|---|---|---|
| student_id: | 47 | 53 | 72 | 61 | 28 | 79 |
| course_id: | 0 | 2 | 0 | 0 | 2 | 2 |
| topic_id: | 0 | 0 | 3 | 2 | 3 | 1 |
| lecture_id: | 0 | 4 | 1 | 8 | 2 | 8 |
| type: | Ppt | Exam | Document | Ppt | Ppt | Pdf |
| marks: | 0 | 44 | 0 | 0 | 0 | 0 |
| mental_state: | 7 | 1 | 1 | 5 | 1 | 1 |
| learning_style: | 3 | 0 | 6 | 3 | 3 | 7 |
| course_completion: | 31 | 42 | 6 | 33 | 96 | 79 |
| opening_time: | 2001-09-09T15:54:12Z | 2001-09-10T17:55:42Z | 2001-09-10T09:18:55Z | 2001-09-10T18:44:07Z | 2001-09-10T22:07:13Z | 2001-09-10T15:18:19Z |
| closing_time: | 2001-09-09T17:14:28Z | 2001-09-10T20:14:13Z | 2001-09-10T09:25:21Z | 2001-09-10T19:02:45Z | 2001-09-11T00:25:22Z | 2001-09-10T18:37:23Z |

Table 2 — Attributes in the Dataset (Some Samples Taken from Dataset)

| | | | | | | |
|---|---|---|---|---|---|---|
| student_id: | 80 | 26 | 82 | 40 | 40 | 6 |
| course_id: | 1 | 2 | 1 | 0 | 2 | 1 |
| topic_id: | 4 | 1 | 3 | 0 | 4 | 4 |
| lecture_id: | 8 | 8 | 7 | 4 | 7 | 0 |
| type: | Ppt | Pdf | Video | Pdf | Pdf | Pdf |
| marks: | 0 | 0 | 0 | 0 | 0 | 0 |
| mental_state: | 4 | 6 | 6 | 2 | 7 | 1 |
| learning_style: | 2 | 4 | 6 | 4 | 1 | 5 |
| course_completion: | 57 | 63 | 14 | 47 | 83 | 62 |
| opening_time: | 2001-09-10T11:16:12Z | 2001-09-10T16:08:08Z | 2001-09-10T10:40:10Z | 2001-09-10T07:25:00Z | 2001-09-10T20:31:43Z | 2001-09-10T19:17:41Z |
| closing_time: | 2001-09-10T11:47:10Z | 2001-09-10T18:40:56Z | 2001-09-10T12:56:09Z | 2001-09-10T08:54:58Z | 2001-09-11T00:07:25Z" | 2001-09-10T22:56:28Z |

Table 3 — Attributes in the Dataset (Some Samples Taken from Dataset)

| | | | | | | |
|---|---|---|---|---|---|---|
| student_id: | 21 | 88 | 87 | 26 | 84 | 93 |
| course_id: | 0 | 2 | 2 | 0 | 0 | 2 |
| topic_id: | 3 | 1 | 4 | 4 | 4 | 3 |
| lecture_id: | 2 | 1 | 0 | 7 | 4 | 2 |
| type: | Exam | Exam | Video | Document | Pdf | Exam |
| marks: | 80 | 38 | 0 | 0 | 0 | 27 |
| mental_state: | 6 | 5 | 5 | 6 | 1 | 3 |
| learning_style: | 3 | 5 | 1 | 7 | 1 | 6 |
| course_completion: | 50 | 36 | 5 | 97 | 84 | 37 |
| opening_time: | 2001-09-10T23:15:25Z | 2001-09-10T16:12:13Z | 2001-09-10T17:08:47Z | 2001-09-10T14:00:29Z | 2001-09-10T18:22:47Z | 2001-09-10T17:27:27Z |
| closing_time: | 2001-09-11T00:14:55Z | 2001-09-10T16:15:45Z | 2001-09-10T19:08:46Z | 2001-09-10T16:13:11Z | 2001-09-10T20:10:25Z | 2001-09-10T20:19:44Z |

in tabular form and some samples taken from dataset eKhool LMS has been enlisted in Table 1,2,3 for a clear demonstration.

**Extraction of the Influential Characteristics of the Learner**

The prediction model input has a large number of attributes that can maximize the execution time and require more amount of system memory. Hence, to avoid these issues the feature extraction process is employed in this research. The influential characteristics are extracted from the learner indicators for boosting the prediction accuracy and the influential characteristics perform the correlation study using the entropy features and statistical features.

***Statistical Features in the Performance Prediction:***

Using statistical analysis, the statistical-based feature selection method determines which input qualities have the strongest correlation with the target variable by assessing each input variable's association with the target variable. In order to establish a strong relationship between the target variables, the prediction model extracts statistical properties such as mean, variance, standard deviation, skewness and kurtosis.

*a) Mean:* The mean is estimated by taking the average of the attributes present in the data, which is mathematically expressed as

$$F_{\mu} = \mu_i = \frac{1}{N}\sum_{i=1}^{N} \mathrm{A}_i^t \qquad \dots (2)$$

where, $\mathrm{A}_i^t$ represents the attributes of the data at $t^{th}$ time instance corresponding to the $i^{th}$ data and $N$ represents the total attributes in the data.

*b) Standard Deviation:* The accuracy of the prediction model is directly impacted by the standard deviation, which assesses the slight fluctuations in the data's properties concerning the desired variables.

$$F_{SD} = SD_i = \sqrt{\frac{\sum_{t=1}^{N}\left(\mathrm{A}_i^t - \mu_i\right)^2}{N-1}} \qquad \dots (3)$$

*c) Variance:* The variance of the attributes is used to estimate the minute variation in the attributes concerning the performance class.

$$F_{\mathrm{var}} = \sigma_i = \frac{\sum_{t=1}^{N}\left(\mathrm{A}_i^t - \mu_i\right)^2}{N-1} \qquad \dots (4)$$

*d) Skewness:* The skewness is used to estimate the unevenness of the attributes about its mean. The values of the skewness can be zero, negative, or positive

$$F_{skew} = E\left[\left(\frac{\mathrm{A}_i^t - \mu_i}{\sigma_i}\right)^3\right] \qquad \dots (5)$$

where, $E$ is the expectation factor. Hence, all these features are combined and mentioned as $F_{stat}$

***Normal Features in the Performance Prediction:***

The normal features of the learners such as student's mark, course ID, topic ID, study material (audio, video, PDF), mode of exam, and mental state of students (stable or unstable), study time taken by the student. Let us denote the normal features as $F_{norm}$ and it is mathematically represented as

$$F_{Tot} = F_{stat} + F_{norm} \qquad \dots (6)$$

These statistical features and normal features are combined to form a feature vector and this feature vector is represented as $F^V$ .

**Learner Prediction using The Proposed Life-BS-Based LightGBM Coupled Neural Network Classifier**

The Light GBM linked NARX neural network is an adaptable framework used to forecast the learner's performance, subsequently functions by calculating the error between the anticipated result and the ground data. The suggested Life-BS optimization approach is used to adjust the weights of the Light GBM coupled NN classifier model based on an error. The NARX classifier is the neural network that the model inherits, and its main benefit is that it has a constrained feedback design, which lowers computational loss when compared to other traditional techniques. The Multilayer Perceptron (MLP) with recurrent loop and time delay is used because gradient descent learning is also found to be more productive in the NARX architecture. This MLP is important for time series predictions because it depends on both the input data and the previous data record. The architecture of NARX NN and their training mode has been depicted in Fig. 2. The input layers, hidden layers, and output layers make up the NARX NN. The input feature vector, retrograded output vector, and postponed external input vector make up the input layer of NARX. Any exterior

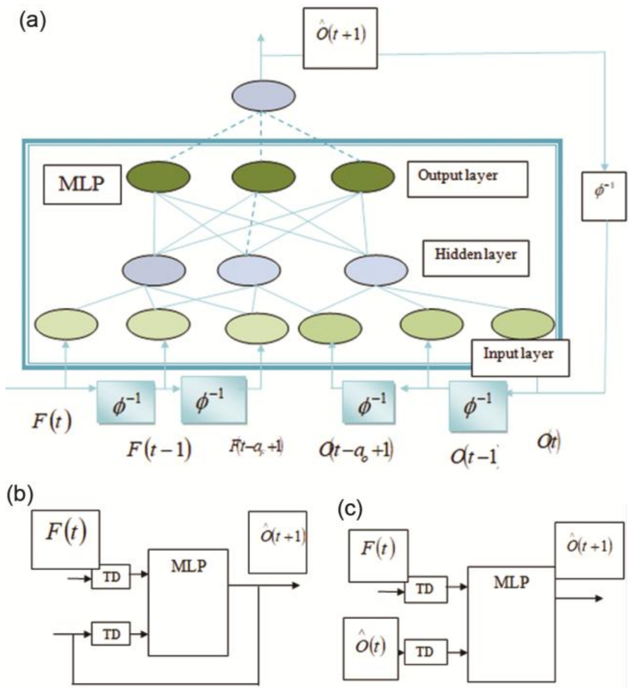



Fig. 2 — a) Architecture of NARX Network, b) Parallel Mode, and c) Series-Parallel

condition can be set using an external variable. The output of the learner's performance prediction using the NARX is denoted as,

$$O(t+1) = f\left(O(t),.....,O(t-a_p);F(t),....F(t-a_F+1)\right) \quad \ldots(7)$$

where, $f(\ )$ represents the nonlinear mapping function of NN, $O(t)$ represents the input of the NARX classifier at the time $t$, and $F(t)$, represent the input of the NARX classifier. The number of input delay and the number of output delays is represented as $a_p$ and $a_F$ respectively. The nonlinear mapping $f(\ )$ is unspecified and it is approximated through the training process of the prediction. The approximation is done by the internal architecture known as MLP as it provides the dynamic structure to learn the non-linear mapping. Two different modes were employed for the training of the NARX Network such as, the series-parallel mode also known as open-loop and the parallel mode known as close-loop. In the close loop, the output is fed back to the feed-forward NN as depicted in Fig. 2. In the open loop, the real output is fed to the NN instead of the estimated output. There are two main advantages to open-loop architecture

It provides a more accurate solution and more precise output as utilizes the true output value.

The second advantage is that the resulting network is purely fed forward and it is trained by using the Life-BS optimization algorithm.

The highly discriminated features extracted from the NARX NN are fed as the input to the LightGBM that performs the accurate prediction of the performance of the students. The basic learner of LightGBM is the DTs that enable the parallel training. The major benefits of the LightGBM include low memory consumption, faster training, and fast processing of the data. To estimate the information gained from the research, the Gradient-based one-sided sampling (GOSS) is utilized that increase the speed of the computation with the reduced number of samples. In this algorithm, the data with higher gradients are increased while small gradient data are removed, which enhances the efficiency of the research model along with the efficient dimension reduction.[28] The improvement in operational efficiency is obtained through the leaf-wise growth strategy that includes the particular depth limitation. The model achieves higher accuracy of the prediction when the split of the tree remains the same.[29]

**Weight Optimization Constraint:**

LightGBM coupled NN is one of the supervised machine learning frameworks, which maps the training data with the test data accurately through the frequent updates in the classifier weights without any topological variations while fixing the activation functions. For the training set, $S = \{(x_1, y_1),(x_2, y_2),...,(x_m, y_m)\}$, the error function be $E_f(\omega, x, y)$, which should be minimized. Generally, the error function is formulated as the mean squared error as given by,

$$E_f(x_i, y_i) = Min\sum_{i=1}^{m} E_f(\omega_i, x_i, y_i) \quad \ldots(8)$$

It is very logical to understand that $E_f(x_i, y_i) \geq 0$ such that the corresponding weight $\omega_i$ is considered as the global optimal solution else, the weight $\omega_i$ that corresponds to the minimal error function is declared as the global minimum. Thus, it is clear that the quality of the trained NN model depends on the error function for a given set of training and test patterns. It is peculiar to understand that the ANN model uses the non-linear minimization constraint, where the error function is the objective function and the search space is defined by the network link weights. Thus, it is essential to devise an algorithm that would render an effective weight set for enhancing the accuracy of the NN classifier.

## Weight Optimization using Brain Rule Selection Algorithm:

The weight optimization of the LightGBM coupled NN is performed based on the proposed Brain rule selection algorithm, which is developed through hybridizing the rule generation characteristics of the BSO[30] and learning-selection characteristics of the LCBO[31]. The rule-generation characteristics and learning-selection characteristics are mimicked by humans when there is a need for global decision-making. Accordingly, humans form groups for effective decision-making through their constant learning from a common group (targets with good skills and knowledge), locating the best target, and constant focus on the mistakes and frequent correction and substitutes for the committed mistakes. The idea behind the proposed brain rule selection algorithm is focused on generating and selecting global decisions for solving any kind of constraint.

### Motivation

The Life-BS algorithm is influenced by the decision-making and problem-solving analytical skills of human beings. Human beings are highly intellectual social primates and they are strategic and smarter. The most important characteristic of human beings they always make an effort to learn new techniques from nature. They can learn from the individual species and these features make human beings superior to the other species. Humans can realize the importance of each species and the steps taken by them to mutual survival. Thus, humans can recognize things better than any other species. Human beings possess high thinking and decision-making capacity, which is superior to all other species. Further human beings possess advanced analyzing skills, which makes them generate more and more ideas for the problems from the mutual interaction process. This decision-making and the idea-generating features of human beings provide the prime motivation behind the proposal of the novel Life-BS algorithm.

### Mathematical *Model:*

Human beings are always influenced by one object or the members, whether they are fellow mates, celebrities, or seniors. If human beings fix their target, they gain deep insight into their objectives and make their best effort to obtain the targets. The steps adopted by them to attain their goals are briefly explained below

#### *Generating Ideas through the Intercommunication Process*

The intercommunication process is one of the intellectual characteristics of human beings. If human beings have a desire to achieve the goal they first seek some of the other individual to obtain some ideas about their task. Humans always prefer to seek ideas from different groups of people with different backgrounds. The new ideas are thus generated by those intercommunication processes. Hence, the First process in attaining the goal is generating ideas through the mutual interaction process.

In the inter-communication process, the group of individuals with diverse backgrounds is considered. Substantial and unpredicted ideas are obtained through this process. The following steps are to be followed in the intercommunication process.

*Step 1:* Gather a group of individuals with different backgrounds for the intercommunication process.

*Step 2:* Initiate the ideas according to the directives framed in the intercommunication process.

*Step 3:* Consider 2 or 3 individuals as the problem owner to pick up the concepts that would be better to resolve the issue.

*Step 4:* The concepts with the higher probability generate hints that aid in evolving the other concepts.

*Step 5:* The owners are now required to select some better ideas from the generated ideas as mentioned in step 4.

*Step 6:* Randomly select the idea and use the functions of these ideas as hints, generating more ideas concerning the directives.

*Step 7:* A good solution is obtained by consolidating the ideas generated in the process.

In the mutual interaction process, there are coordinators, the group of individuals, and the individual, who seek ideas for achieving their goals. The directives of the idea are given below:

a) *Stop Judging the Ideas:* According to this directive every idea generated by the individuals is treated as equal and no idea should be commented as a bad idea.

b) *Share the Ideas:* This directive forces us to share the ideas that come to the mind during the intercommunication process.

c) Cross Fertilize: According to this directive new ideas can be generated by considering the high probability ideas as clues.

d) *Quality depends on Quantity:* This rule states that it is impossible to bring out ideas with good quality without generating large quantities of ideas.

The newly generated idea from the mutual interaction process is given as

The new idea generated by the mutual interaction process is given in the following equation

$$\mathrm{P}_{MI}^{new} = \mathrm{P}_{MI}^{sel} + \tau * G(\mu,\sigma) \qquad \ldots (9)$$

The $\mathrm{P}_{MI}^{new}$ is the newly generated ideas, $\mathrm{P}_{MIj}^{sel}$ is the idea selected to generate the new idea in $j^{th}$ dimension, $G(\mu,\sigma)$ represents the Gaussian random function consisting of the variance $\sigma$ and mean $\mu$, $\tau$ is the coefficients that weight the contribution of Gaussian value. This $\tau$ is mathematically estimated as

$$\tau = \log sig\left(\left(0.5 * I^{\max} - I^{current} / k\right) * \Re(\ )\right) \qquad \ldots (10)$$

The logarithmic sigmoid transfer function is determined as $\log sig(\ )$, $I^{\max}$ is the maximum iteration, and $I^{current}$ is the current iteration $k$ is for altering function slope of $\log sig(\ )$ and $\Re(\ )$ is the random variable between (0,1). The best solution is obtained through the following process.

***Gaining Knowledge from the Best Group***

Humans make their effort to create something creative and to derive ideas for the goals under consideration by observing the efficiency of superior and intelligent people. Let us assume that the population or ideas $\mathrm{P}$ with the categorized fitness value. Hence, the idea of learning from the best features is mathematically represented as

$$\mathrm{P}_j^{'} = \sum_{\mathrm{K}=1}^{\mathrm{N}} \frac{\left[\Re(\mathrm{K}) * \mathrm{P}_{\mathrm{K}}\right]}{\mathrm{N}} \qquad \ldots (11)$$

These are the $\mathrm{N}$ algorithm's parameters, which are the same as ceil of the population's square root in order to solve the problem. The random variable $\Re$ is determined by a $\mathrm{K}$ range of 1 to $\mathrm{N}$. $\mathrm{P}_j$ is thought of as the concepts created during the process by $j^{th}$ search agents and $\mathrm{P}^{'}$ represents the updated form. If and only if $\mathrm{P}_j^{'}$ achieves greater fitness than $\mathrm{P}_j$, $\mathrm{P}_j$ will be updated. The search agents that are now available are displayed in the circle's center. The random numbers define the level of effect that the common best search $\mathrm{N}$ agents have over the search agent.

***Determining the Current Target to Attain the Goal***

It is known that attaining a massive target requires a lot of time and perseverance, which demonstrates the complexity of the targeted goal. Hence, it is beneficial to set the current targets, which lead us to attain the main target. Further, setting the current target provides insight into how to attain a better position than the current target. Hence, it is important to concentrate on the current target to attain the final goal. This idea is implemented with the following calculations

$$\mathrm{P}_j^G = \mathrm{P}_j + \Re(\ ) * F^{better} + \Re(\ ) * F^{best} \qquad \ldots (12)$$

In the above equation, the $F^{better}$ determines the better fitness value and $F^{best}$ determines the better fitness value and it is estimated by the following expression

$$F^{better} = L_1 * R_1 * \left(\mathrm{P}_1 - \mathrm{P}_J\right) \qquad \ldots (13)$$

$$F^{best} = L_2 * R_1 * \left(\mathrm{P}_{j-1} - \mathrm{P}_J\right) \qquad \ldots (14)$$

Here, $L_1$ and $L_2$ differ linearly from 0 to 1 and from 1–0 and it is calculated by using the following equation. $R_1$ is constant and the value is 2.35, $\mathrm{P}_1$ represents the best position of the search agent.

$$L_1 = \frac{1 - \left(C_j - 1\right)}{\left(C_{\mathrm{N}} - 1\right)} \qquad \ldots (15)$$

$$L_2 = 1 - L_1 \qquad \ldots (16)$$

$C_j$, demonstrates the current chances and $C_{\mathrm{N}}$ determines the number of chances, the $R_1$ is constant and it is determined as 2.35.

***Analyzing Mistakes***

Humans inherit the natural intelligence to evaluate things and proper analysis is carried out by them to find the alternate optimal solution if they struck with the previous techniques or the established techniques fail to provide an appropriate solution. They can able to approach the same problem differently. It enhances the exploration part of the algorithm and tries to solve the process in a completely different process. The updated position is mathematically represented as

$$P_j^{'} = P_{max} - \left(P_j - P_{min}\right) * \Re(\ ) \quad \dots (17)$$

The aforementioned technique is known as the AVI escape technique and it is used as the generalized technique to enhance the exploration algorithm. The $P_{max}$ and $P_{min}$ are upper and lower bound.

***Integration of the Ideas to Obtain The Global Best Solution***

After realizing mistakes, the best ideas obtained from the mutual interaction process are integrated with ideas selected from the opinion of the experts, which provides the global best solution for the optimization issues. The integration process is mathematically represented in the following equation as mentioned in reference[32]

$$P^{t+1} = 0.5P^{G} + 0.5P_{MI}^{new} \quad \dots (18)$$

Substituting equation (9) and (12) in (18)

$$P^{t+1} = 0.5\left[P_j + \Re(\ ) * F^{better} + \Re(\ ) * F^{best}\right] + 0.5\left[P_{MI}^{sel} + \tau * G(\mu, \sigma)\right] \quad \dots (19)$$

The equation (19) represents the global optimal solution obtained from the proposed Life-BS optimization algorithm. Hence, the weight update is carried out by using this final updated equation.

***Termination***

The above steps are attained in the loop until the globally optimal solution has occurred. Hence, the classifier achieves better performance with improved prediction accuracy through the proposed optimization algorithm. The Pseudo-code for the Life-BS algorithm is explained below in Algorithm 1.

**Algorithm 1:** Pseudo Code of the Life-BS Optimization

| S. No | |
|---|---|
| 1 | Input: $P_j$ |
| 2 | Result: $P^{t+1}$ |
| 3 | Declare the population of solutions |
| 4 | Derive newly generated ideas through the mutual interaction process $P_{MI}^{new}$ |
| 5 | Gain knowledge from the best group $P_j^{'}$ |
| 6 | Estimate the fitness value |
| 6 | Determine the ideas to attain a current target $P_j^{G}$ |
| 7 | Update the position by analyzing the mistake $P_j^{'}$ |
| 8 | Estimate the best solution by integrating the ideas obtained from the mutual interaction process and the expert opinion $P^{t+1}$ |
| 9 | Attain the global best solution $P^{t+1}$ |
| 10 | End |

## Results and Discussions

This section explains the outcomes achieved with the suggested Life-BS-based NN and the current performance prediction model. The experimental evaluation is carried out on a PC running Windows 10 with 16 GB of RAM and MATLAB loaded. The dataset is the lively-generated real time dataset with 30000 available data, collected and organized from the e-khool LMS, which is not publicly available. The dataset is categorized with the attributes such as the student ID, course ID, topic ID, lecture ID, type of the lecture, marks, mental state, learning style, course completed and the last course opening and the closing time. The total available data with all the described attributes are separated as the training and the testing data to perform the student's performance prediction research. Here utilization of blockchain results in reliability, data integrity, and immutability. For example, protects individual assets, guarantees that scholarly information is secured against illegitimate modification, for instance, certificate forgery, certificate manipulating and falsification, accelerating the preparing of college scholastic records, transferring the academic records between the educational institution and finally it guarantee straightforward graduation necessities that cannot be altered without legitimate approval. This is a part of the security and legitimate confirmation of historical data of students. Here authors have demonstrated some samples taken from the ekhool LMS dataset on different features mentioned in the section 'Read the learner indicators'.

**Performance Metrics**

Four metrics, Mean Absolute error (MAE), Kappa, Mean square error (MSE), and root mean square error (RMSE), are used to assess the efficacy of the suggested performance prediction technique

*a) MSE:* MSE is the squared average of actual value minus projected value.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} RV - PV \quad \dots (20)$$

where, $RV$ represents the real value and the $PV$ represents the predicted value.

*b) RMSE:* RMSE is an error of the average difference between the actual and anticipated values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n} AV - PV} \qquad \ldots (21)$$

*c) MAE:* The average of the significant values in the dataset to the predicted values.

*d) Kappa:* The Kappa (value or statistic) is a metric that compares an Observed Accuracy with an Expected Accuracy (random chance). The kappa statistic is utilized not only to assess a single classifier, but also to assess classifiers amongst themselves. Moreover, it considers, random chance (agreement with a random classifier), that normally means it is less misleading as compared to simply utilizing accuracy as a metric. The Kappa score, also known as Cohen's Kappa coefficient. The value of Kappa ranges from -1 to 1. Kappa can be measured by following formula:-

Kappa = (observed accuracy - expected accuracy)/(1 - expected accuracy) … (22)

**Performance Analysis of Life-BS based LightGBM Coupled NN Classifier**

This section elucidates the performance analysis of the Life-BS-based LightGBM coupled with an NN classifier with measures such as the MSE, RMSE, MAE and kappa coefficient.

***Performance Analysis with Delay in Days***

*Performance Analysis for Course-1:*

The MSE for the proposed Life-BS-based LightGBM coupled NN classifier is given in Fig. 3. The MSE obtained in course 1 is 3.675, 3.364, 3.266, 3.131, 2.969, and 2.477, for 50 epochs, 100 epochs, 150epochs, 200epochs, 250epochs, and 300epochs, respectively with five days of delay. While the RMSE attains 1.917, 1.834, 1.807, 1.769, 1.723, and 1.574

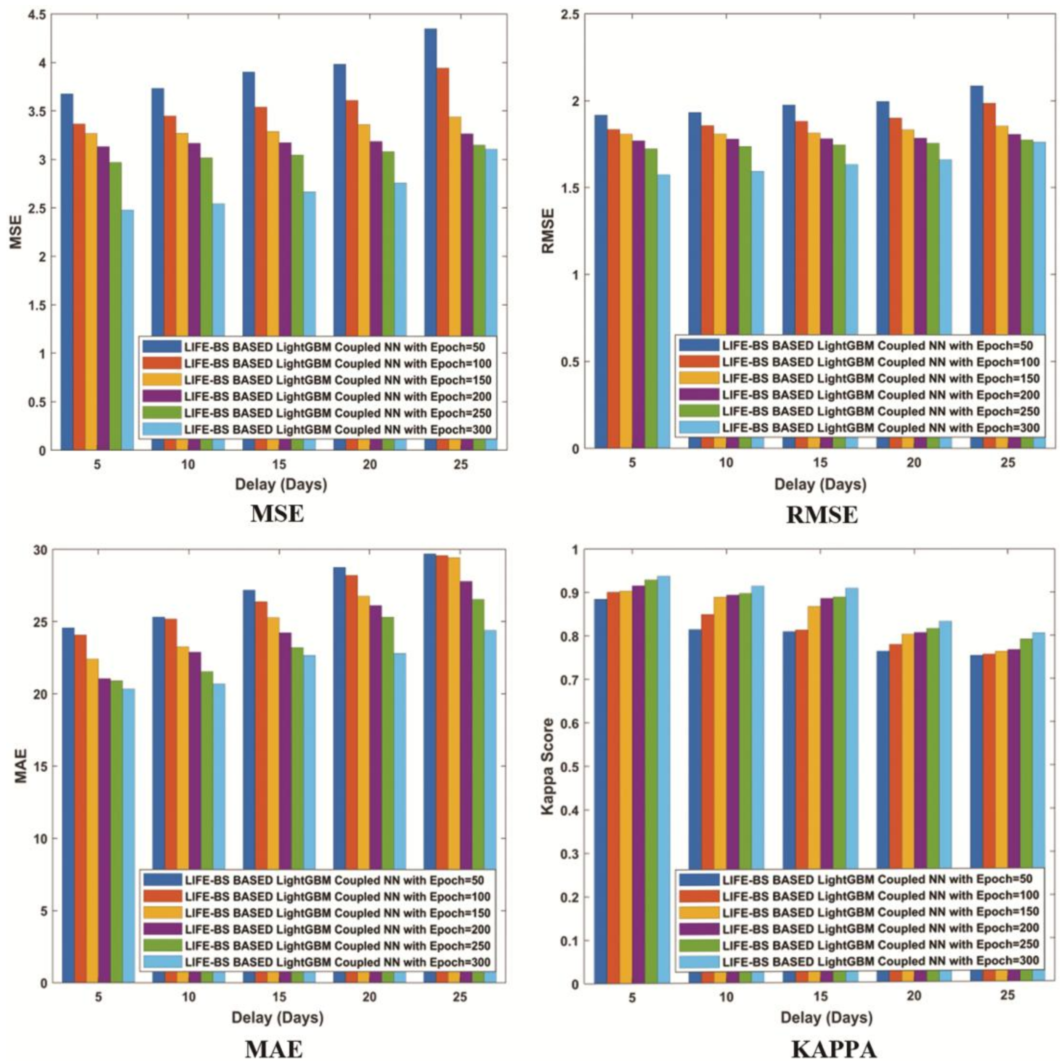



Fig. 3 — Performance Analysis of the Course-1

for the delay of five days at epochs 50, 100, 150, 200, 250, and 300 respectively, the MAE attains 24.57, 24.08, 22.41, 21.06, 20.91, and 20.34 with the respective epochs for the delay of five days. The Kappa coefficient in course 1 is 0.885, 0.901, 0.903, 0.915, 0.929, and 0.938 for the delay of five days with the epochs 50, 100, 150, 200, 250, and 300 respectively.

*Performance Analysis for Course-2:*

The MSE obtained in course 2 (Fig. 4) achieves 3.991, 3.426, 3.41, 3.089, 2.893, and 2.858 for the delay of five days with epochs 50, 100, 150, 200, 250, and 300, respectively. While the RMSE attains 1.998, 1.851, 1.847, 1.758, 1.701, and 1.691 for the delay of five days at epochs 50, 100, 150, 200, 250, and 300 respectively, the MAE attains 23.44, 23.22, 21.52, 20.67, 20.35, and 20.01 with the respective epochs for the delay of five days. The Kappa coefficient in course 2 is 0.875, 0.882, 0.883, 0.886, 0.909, and 0.934 for the delay of five days with the epochs 50, 100, 150, 200, 250, and 300 respectively.

*Performance Analysis for Course-3:*

For course-3 at different epochs, the MSE of the proposed Life-BS based LightGBM coupled NN classifier is 3.564, 3.479, 3.053, 3.037, 2.876, and 2.769 for the delay of five days at respective epochs (Fig. 5). While the RMSE attains 1.887, 1.863, 1.747, 1.742, 1.695, and 1.664 for the delay of five days at epochs 50, 100, 150, 200, 250, and 300 respectively, the MAE attains 24.45, 23.05, 22.42, 22.08, 21.19, and 20.91 with the respective epochs for the delay of five days. The Kappa coefficient in course 3 is 0.819, 0.862, 0.903, 0.927, and 0.939 for the delay of five days with the epochs 50, 100, 150, 200, 250, and 300 respectively.

**Comparative Analysis**

The comparative techniques involved are the Life-BS based LightGBM coupled NN classifier and the

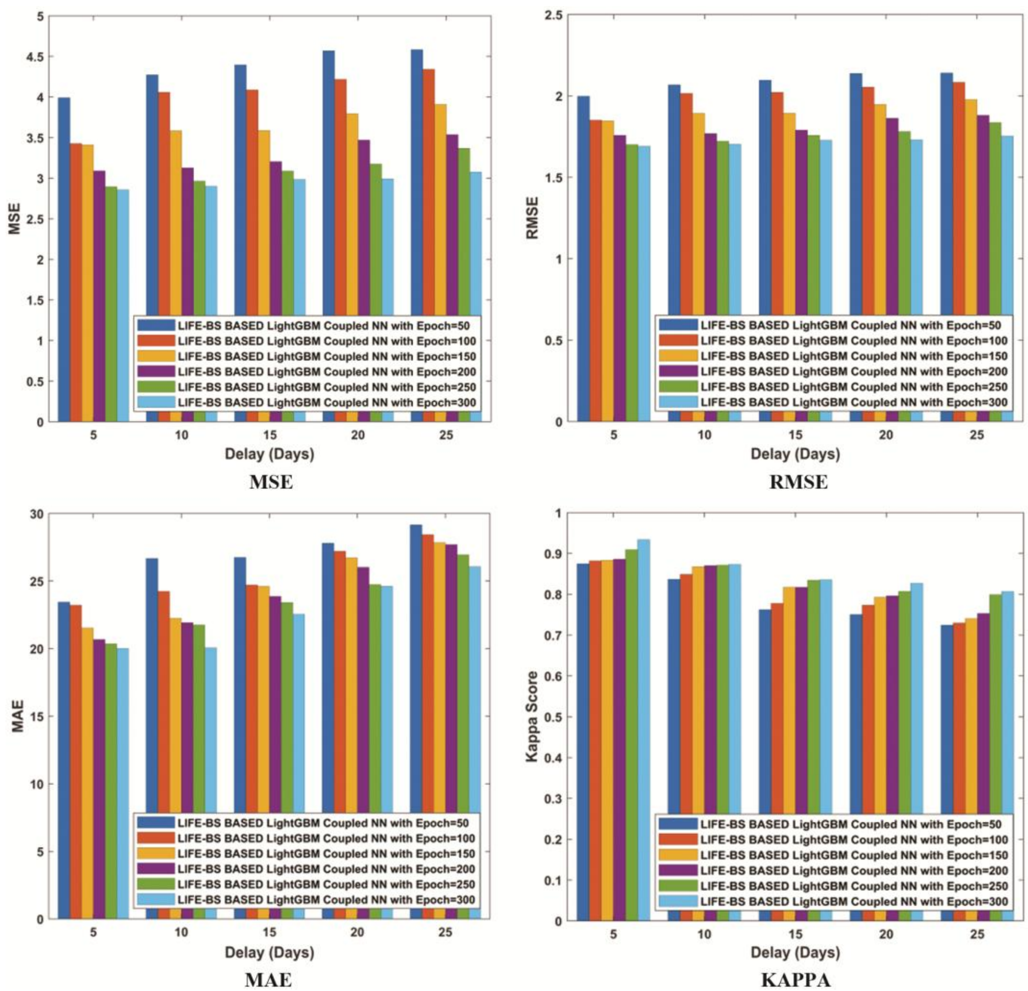



Fig. 4 — Performance analysis of Course 2

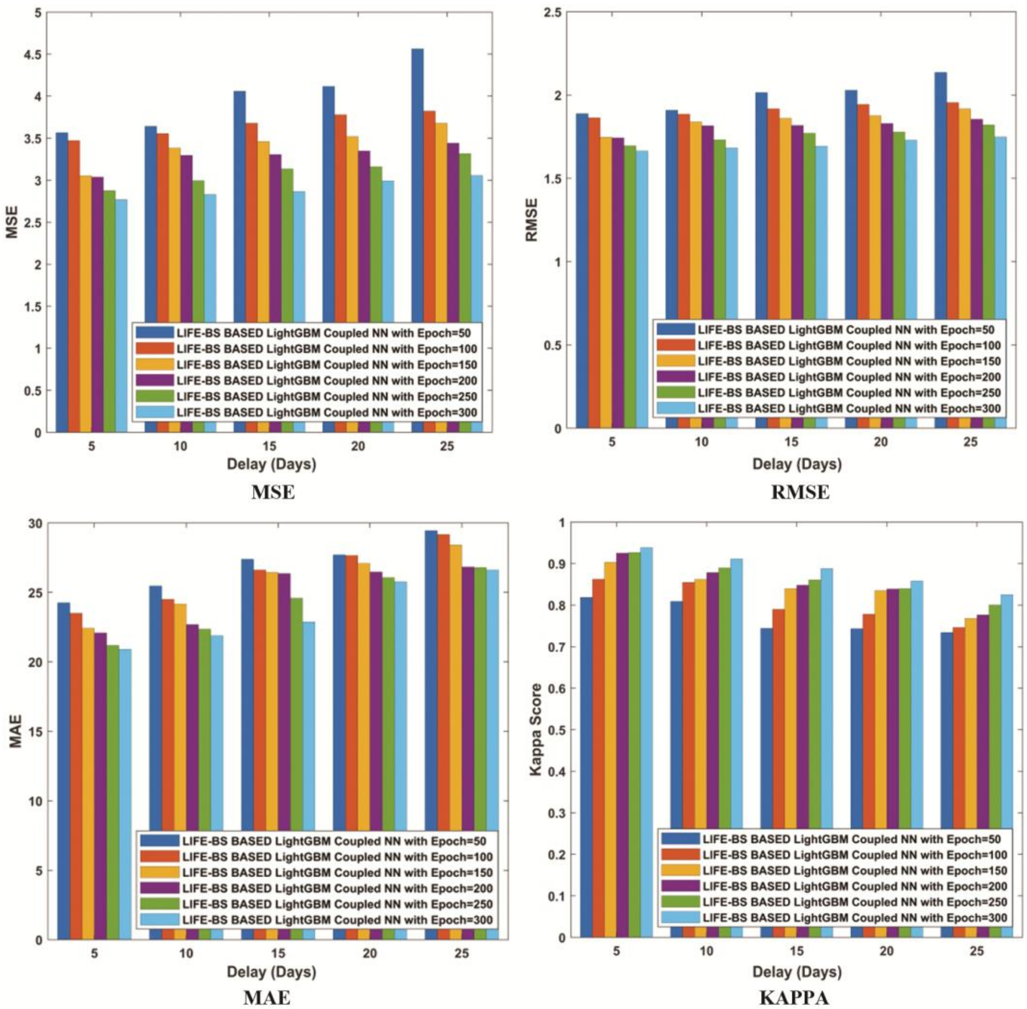



Fig. 5 — Performance analysis of the Course-3

existing methods, such as Light GBM coupled NN with Brain Storm[30], Light GBM coupled NN with LCBO[31], LightGBM coupled NN[33], LightGBM [34], NARX Neural Network[35]. In addition, the performance of the Life-BS-based LightGBM coupled NN classifier is analyzed compared to the conventional methods.

***Comparative Analysis with Delay in Days***

*Comparative Analysis for Course-1:*

The comparative analysis for course 1 is evaluated in this section and the MSE for the proposed Life-BS based LightGBM coupled NN classifier is illustrated in Fig. 6. The MSE for the classifier shows an improvement with the existing methods such as NARX NN, LIghtGBM, LightGBM coupled NN, Light GBM coupled NN with LCO, Light GBM coupled NN with Brainstorm is 7.84, 5.14, 4.95, 4.05 and 0.46 for the delay of five days, respectively. The RMSE shows improvement of 1.27, 0.88, 0.86, 0.71, and 0.09 for the delay of five days, respectively, and the MAE shows improvement of 4.61, 1.52, 0.98, 0.75, and 0.42 with the respective methods for the delay of five days. The Kappa coefficient in course1 shows an improvement of 0.12, 0.07, 0.02, 0.018, and 0.016 for the delay of five days with the respective methods.

*Comparative Analysis for Course-2:*

The comparative analysis for course 2 is evaluated in this section and the MSE for the proposed Life-BS based LightGBM coupled NN classifier is illustrated in Fig. 7. The MSE for the classifier shows an improvement with the existing methods such as NARX NN, LIghtGBM, LightGBM coupled NN, Light GBM coupled NN with LCO, Light GBM coupled NN with Brainstorm is 6.26, 4.96, 4.71, 4.35, and 0.28, respectively for the delay of five days.

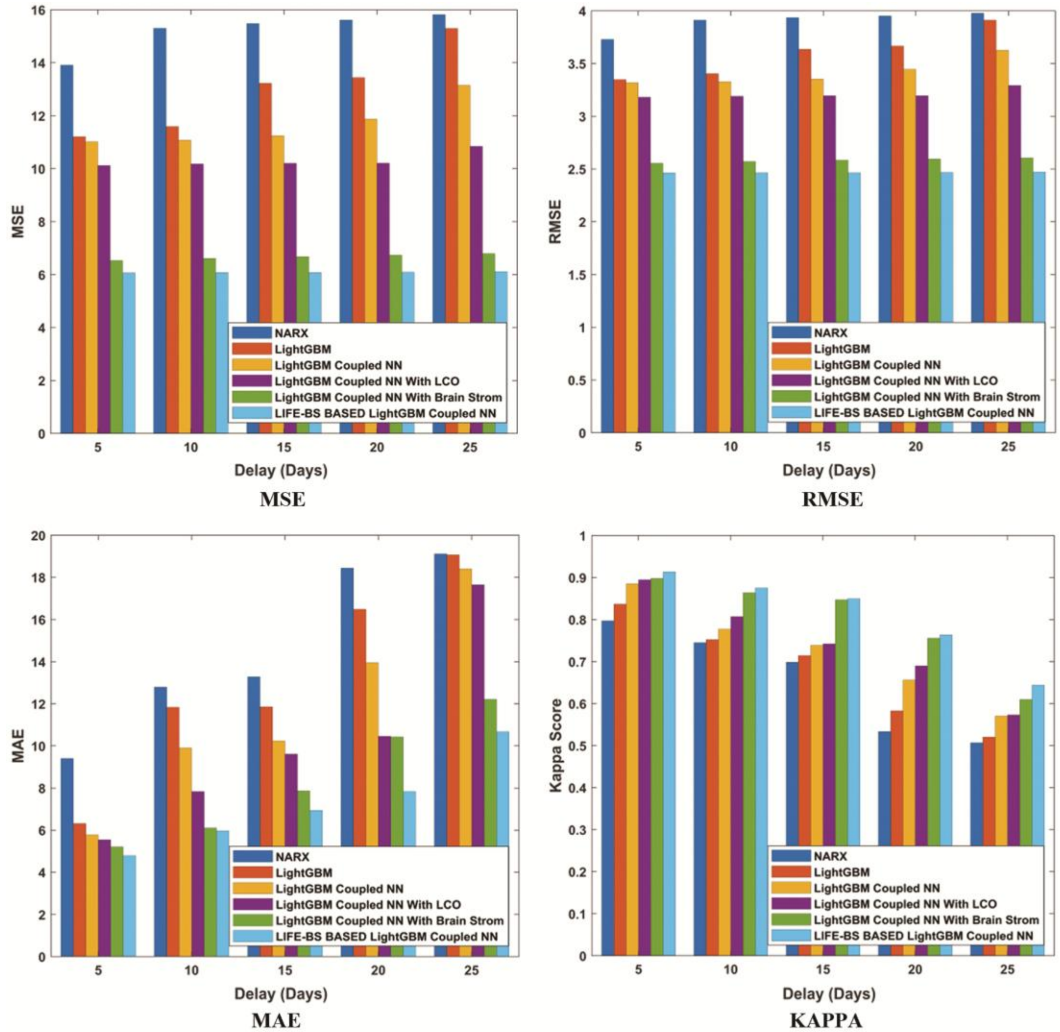
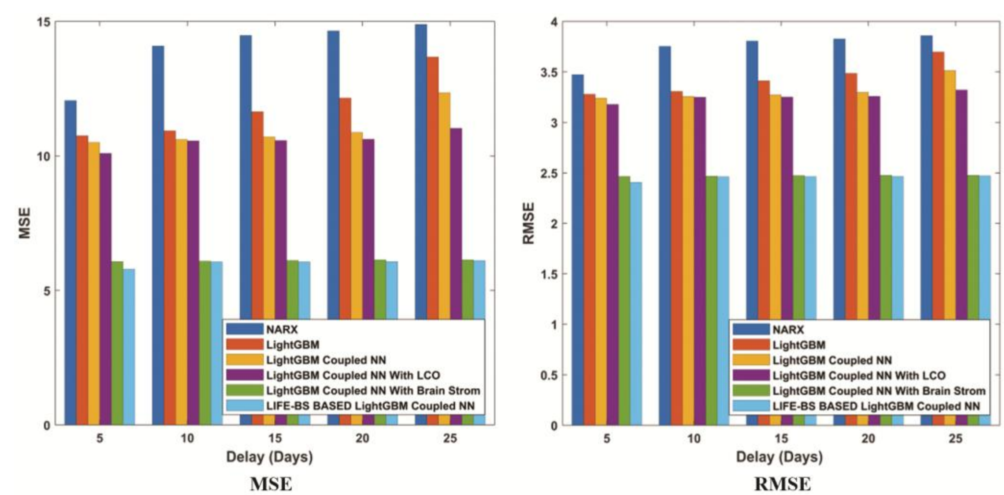



Fig. 6 — Comparative analysis of the Course-1




(*Contd*.)

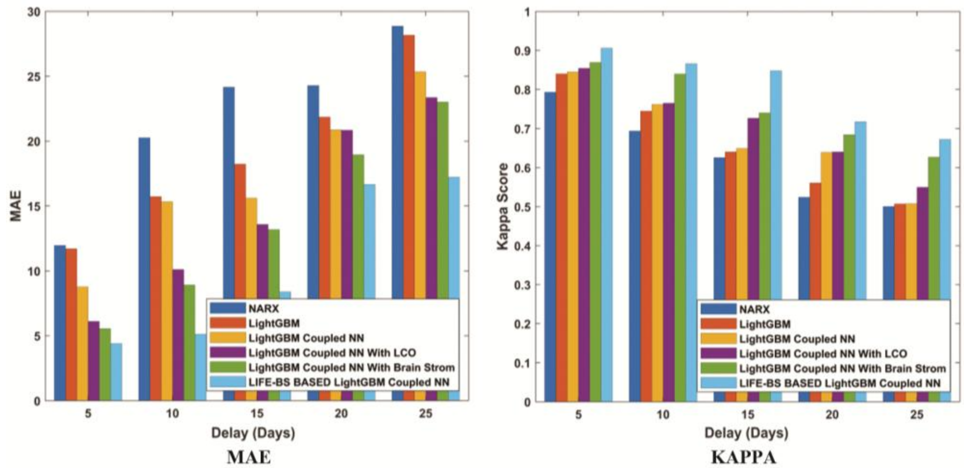



Fig. 7 — Comparative analysis of Course 2

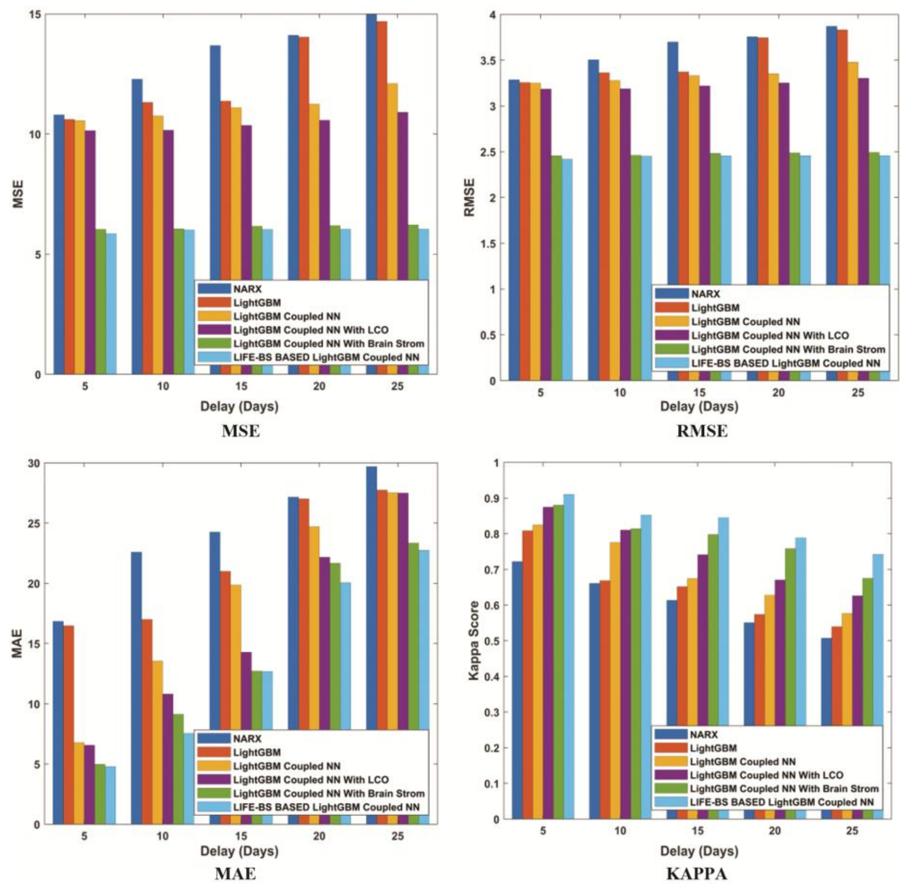



Fig. 8 — Comparative analysis of the Course-3

RMSE shows improvement of 1.07, 0.87, 0.83, 0.77, and 0.06 for the delay of five days, respectively, and the MAE improvement of 7.56, 7.30, 4.37, 1.71, and 1.15 with the respective methods for the delay of five days. The Kappa coefficient in course-2 shows an improvement of 0.113, 0.066, 0.061, 0.052, and 0.037 for the delay of five days with respective methods.

*Comparative Analysis for Course-3:*

The comparative analysis for course 3 is evaluated in this section and the MSE for the proposed Life-BS based LightGBM coupled NN classifier is illustrated in Fig. 8. The MSE for the classifier shows an improvement with the existing methods such as NARX NN, LIghtGBM, LightGBM coupled NN,

Table 4 — Comparative Discussion

| Course | | NARX method[35] | Light GBM[34] | LightGBM coupled NN[33] | LightGBM coupled NN + LCO[31] | LightGBM coupled NN + brain storm[30] | Proposed Life-BS-based LightGBM coupled NN model |
|---|---|---|---|---|---|---|---|
| 1 | MSE | 13.907 | 11.206 | 11.021 | 10.120 | 6.530 | 6.069 |
| 2 | MSE | 12.058 | 10.754 | 10.505 | 10.098 | 6.075 | 5.793 |
| 3 | MSE | 10.801 | 10.606 | 10.557 | 10.140 | 6.036 | 5.853 |
| 1 | RMSE | 3.729 | 3.348 | 3.320 | 3.181 | 2.555 | 2.464 |
| 2 | RMSE | 3.472 | 3.279 | 3.241 | 3.178 | 2.465 | 2.407 |
| 3 | RMSE | 3.286 | 3.257 | 3.249 | 3.184 | 2.457 | 2.419 |
| 1 | MAE | 9.404 | 6.319 | 5.779 | 5.543 | 5.215 | 4.794 |
| 2 | MAE | 11.965 | 11.704 | 8.771 | 6.109 | 5.554 | 4.400 |
| 3 | MAE | 16.849 | 16.478 | 6.776 | 6.567 | 4.981 | 4.794 |
| 1 | KAPPA COEFFICIENT | 0.797 | 0.837 | 0.885 | 0.895 | 0.898 | 0.913 |
| 2 | KAPPA COEFFICIENT | 0.793 | 0.840 | 0.845 | 0.854 | 0.869 | 0.906 |
| 3 | KAPPA COEFFICIENT | 0.722 | 0.809 | 0.825 | 0.875 | 0.880 | 0.911 |

Light GBM coupled NN with LCO, Light GBM coupled NN with Brainstorm is 4.94, 4.75, 4.70, 4.29, and 0.18 for the delay of five days, respectively. The RMSE shows improvement of 0.87, 0.84, 0.83, 0.77, and 0.04 for the delay of five days, respectively, and MAE shows improvement of 12.05, 11.68, 1.98, 1.77 and 0.19 with the respective methods for the delay of five days. The Kappa coefficient in course2 shows an improvement of 0.188, 0.102, 0.086, 0.036, and 0.030 for the delay of five days with respective methods.

#### Comparative Discussion

A tabular description of the suggested technique in comparison to existing methods is depicted in Table 4, including Deep LSTM, RNN, Deep learning, and Auto regression NARX method.

## Conclusions and Future Scope

The research article provides the prediction of the learner's performance by using the Life-BS-based LightGBM coupled NN model. A significant part of the research lies in the tuning of the hyper-parameters with the Brain rule selection algorithm, which boosts the accuracy of the classifier. Furthermore, by lowering the dimensionality of the data, the feature extraction approach is developed in this study to reduce the computational complexity of the prediction framework. The suggested Life-BS-based LightGBM coupled NN model is shown to be effective by the experimental assessment and shown better performance in terms of performance indicators such as RMSE, MSE, MAE and Kappa. Advantages of utilizing blockchain are reliability, data integrity and immutability. In Future work this proposed model can be further extended either by adding the number of courses to check the variation on performance metrics or adding more features for assessing the student performance.

## Competing Interests

Authors declare that during this project completion there was not competing interests in between authors. All authors have read and agreed to the final version of the manuscript.

## References


1 Rakic S, Tasic N, Marjanovic U, Softic S, Lüftenegger E & Turcin I, Student Performance on an E-learning platform: mixed method approach, *Int J Emerg Technol Learn*, **15(2)** (2020).

2 Wang X, Mei X, Huang Q, Han Z & Huang C, Fine-grained learning performance prediction via adaptive sparse self-attention networks, *Inf Sci*, **545** (2021) 223–40.

3 Azzi I, Jeghal A, Radouane A, Yahyaouy A & Tairi H, A robust classification to predict learning styles in adaptive E-learning systems, *Educ Inf Technol*, **25(1)** (2020) 437–48.

4 Ullah N, Mugahed Al-Rahmi W, Alzahrani A I, Alfarraj O & Alblehai F M, Blockchain technology adoption in smart learning environments, *Sustainability*, **13(4)** (2021) 1801.

5 Aydoğdu Ş, Predicting student final performance using artificial neural networks in online learning environments, *Educ Inf Technol*, **25(3)** (2020) 1913–27.

6 Bhutto E S, Siddiqui I F, Arain Q A & Anwar M, Predicting students' academic performance through supervised machine learning, in *Int Conf Info Sci Commun Technol* (IEEE) 2020), 1–6.

7 Ostapowicz M & Żbikowski K, Detecting fraudulent accounts on blockchain: A supervised approach, in Web Information Systems Engineering–WISE 2019: Proceedings of *20th International Conference* (Springer International Publishing) 19–22 January 2020.

8 Liu W, Xu W, Zhan X, Liu W & Cheng W, Student performance prediction by LMS data and classroom videos, in *2020 15th Int Conf Comput Sci Edu* (IEEE) 2020, 535–539.

9 Ali M, Raza S A, Qazi W & Puah C H, Assessing e-learning system in higher education institutes: Evidence from structural equation modeling, *Interact Technol Smart Educ*, **15(1)** (2018) 59–78.

10 Ubaka-Okoye M N, Azeta A A, Oni A A, Okagbue H I, Nicholas-Omoregbe O S & Chidozie F, Blockchain framework for securing e-learning system, *Institutions*, **27** (2020) 28.

11 Nora A & Snyder B P, Technology and higher education: The impact of e-learning approaches on student academic achievement, perceptions and persistence, *J Coll Stud Retent: Res Theory Pract*, **10(1)** (2008) 3–19.

12 Yeop Y H, Othman Z A, Huda S N, Abdullah S, Mokhtar U A, Fauzi W F P & Ahmad N, Key Factors to Implement BYOD in Schools, in *Cyber Resilience Conference* (Putrajaya, Malaysia) 2018, 1–3, doi: 10.1109/ CR. 2018.8626864.

13 Silva S, Pires F & Bernardino J, Editorial Platform in Blockchain for Application in Higher Education, in *ICETE* **(1)** (2019) 221–227.

14 Arndt T, *Empowering University Students with Blockchain-Based Transcripts* (International Association for Development of the Information Society) 2018.

15 Duan B, Zhong Y & Liu D, Education application of blockchain technology: Learning outcome and meta-diploma, in *2017 IEEE 23rd Int Conf on Parallel and Distributed Sys*tems (IEEE) 2017, 814–817.

16 Yannibelli V, Godoy D & Amandi A, A genetic algorithm approach to recognise students' learning styles, *Interact Learn Environ*, **14(1)** (2006) 55–78.

17 Feldman J, Monteserin A & Amandi A, Automatic detection of learning styles: State of the art, *Artif Intell Rev*, **44(2)** (2015) 157–86.

18 Zatarain-Cabada R, Barrón-Estrada M L, Angulo V P, García A J & García C A, A learning social network with recognition of learning styles using neural networks, in *Proc Adv Pattern Recognit: Second Mexican Conf Pattern Recognit* (Springer Berlin Heidelberg) 27–29 September 2010.

19 Wolff A, Zdrahal Z, Herrmannova D, Kuzilek J & Hlosta M, Developing predictive models for early detection of at-risk students on distance learning modules, (2014).

20 Asif R, Merceron A, Ali S A & Haider N G, Analyzing undergraduate students' performance using educational data mining, *Comput Educ*, **113** (2017) 177–194.

21 Agrawal H & Mavani H, Student performance prediction using machine learning, *Int J Engg Res Tech*, **4(03)** (2015) 111–3.

22 ekhool data, https://ekhool.com/success-client.php?id=5, (May 2021)

23 Anthony M, Bartlett P L & Bartlett P L, *Neural network learning: Theoretical foundations* (Cambridge: Cambridge University Press) 1999.

24 Khatri A, Gaba A, Rana K P & Kumar V, A novel life choice-based optimizer, *Soft comput*, **24** (2020) 9121–9141.

25 Xue J, Wu Y, Shi Y & Cheng S, Brain storm optimization algorithm for multi-objective optimization problems, In Advances in Swarm Intelligence: *Proc Third Int Conf* (Springer Berlin Heidelberg) 17–20 June 2012.

26 Alzubi A, Learner performance prediction in the e-learning platform using the optimized deep long short-term memory classifier, *Int J Wavelets Multiresolution Inf Process*, **20(02)** (2022) 2150051, doi: https://doi.org/10.1142/ S021969132150051X.

27 Srinivas K, Prediction of e-learning efficiency by deep learning in E-khool online portal networks, *Multimed Res*, **3(4)** (2020) 12–23.

28 Ke G, Meng Q, Finley T, Wang T, Chen W, Ma W, Ye Q & Liu T Y, Lightgbm: A highly efficient gradient boosting decision tree, *Adv Neural Inf Process Syst*, **30** (2017).

29 Bentéjac C, Csörgő A & Martínez-Muñoz G, A comparative analysis of gradient boosting algorithms, *Artif Intell Rev*, **54** (2021) 1937–1967.

30 Shi Y, Brain storm optimization algorithm, In Advances in Swarm Intelligence: Proceedings *of Second Int Conf* Part I (Springer Berlin Heidelberg) 12–15 June 2011.

31 Khatri A, Gaba A, Rana K P & Kumar V, A novel life choice-based optimizer, *Soft comput*, **24** (2020) 9121–9141.

32 Binu D & Kariyappa B S, Rider-deep-LSTM network for hybrid distance score-based fault prediction in analog circuits, *IEEE Trans Ind Electron*, **68(10)** (2020) 10097–10106.

33 Gao H, Qiu S, Fang J, Ma N, Wang J, Cheng K, Wang H, Zhu Y, Hu D, Liu H & Wang J, Short-term prediction of PV power based on combined modal decomposition and NARX-LSTM-LightGBM, *Sustainability*, **15(10)** (2023) 8266.

34 Bairamova D, predicting course grades of students'academic performance using the LightGBM regressor, *SDU Bulletin: Natural and Technical Sciences*, **62(1)** (2023) 34–47.

35 Boussaada Z, Curea O, Remaci A, Camblong H & Mrabet B N, A nonlinear autoregressive exogenous (NARX) neural network model for the prediction of the daily direct solar radiation, *Energies*, **11(3)** (2018) 620.