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# Design of a Deep-Learning Model to Improve Learning Capabilities of LD Children via Statistical Modelling of Examination Behavioral Patterns

**Masooda Modak***
Computer Engineering Department at South Indian Graduate School of Technology, Mumbai, India
E-mail: masoodamodak29@gmail.com
ORCID iD: http://orcid.org/0000-0002-6071-8159
*Corresponding Author

**Prachi Gharpure**
SVKM's NMIMS University, Indore Campus, India
E-mail: masoodamodak29@gmail.com
ORCID iD: http://orcid.org/0000-0002-9348-2779

**M Sasikumar**
CDAC, Santacruz, India
E-mail: the.little.sasi@gmail.com
ORCID iD: http://orcid.org/0000-0002-7352-3254

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**Abstract:** Students with learning disorders (LD) are unable to perform certain set of tasks due to their difficulty in understanding & interpreting them. These tasks include, but are not limited to, solving simple Mathematical identities, understanding English Grammar related questions, spelling certain words, arranging words in sequence, etc. A wide variety of system models are proposed by researchers to analyze such issues with LD students, and recommend various remedies for the same. But a very few of these models are designed for end-to-end continuous learning support, which limits their applicability. Moreover, even fewer system models are designed to improve capabilities of LD students, via modification of system's internal parameters. To cater these issues, a novel deep-learning model (DL2CSMBP) is proposed in this text, which assists in incrementally improving learning capabilities of LD children via statistical modelling of examination behavioural patterns. The model initially proposes design of a novel examination system that generates question sets based on student's temporal performance, and collects their responses via an LD-friendly approach. These responses are processed using a deep learning model that extracts statistical characteristics from student responses. These characteristics include question skipping probability, percentage of correct answers, question revisit probability, time spent on each question, un-attempted questions, & frequently skipped question types. They were extracted from 12 different question types which include Basic English Grammar, Medium English Grammar, Advanced English Grammar, direct comprehension, inference comprehension, vocabulary comprehension, sequencing, spelling, synonyms, Mathematics (addition & subtraction), and finding the odd Man out. The results of these questions were evaluated for 80+ LD students, and their responses were observed. Based on these responses a customized 1D convolutional Neural Network (CNN) layer was trained, which assisted in improving classification performance. It was observed that the proposed model was able to identify LD students with 95.6% efficiency. The LD students were able to incrementally improve the performance by attempting a series of exam sessions. Due to this incremental performance improvement, the LD students were able to cover 28% more questions, and answer almost 97% of these questions with precision & correctness. Due to such promising results, the system is capable of real-time deployment, and can act as an automated schooling tool for LD students to incrementally improve their examination performance without need of medical & psychological experts. This can also assist in reducing depression among LD students, because they don't need to interact with a physical doctor while improving their LD condition in real-time, thus suggesting its use in non-intrusive medical treatments of these students.

**Index Terms:** Learning Disability, Deep Learning, Statistical Modelling, Behavioral patterns

 

## 1. Introduction

Learning Disorders (LD) in students include conditions like dyslexia, dysgraphia, dyscalculia, auditory processing disorder, language processing disorder, Nonverbal learning disabilities, and visual perceptual/visual motor deficit disorders. It is observed that nearly 3% to 10% of students suffer from one of these disorders, which restricts their capabilities to learn certain life skills. The effects of these disorders are reversible, and can be cured using therapy, recurrent practice, consistency, and other techniques. In order to identify presence of these disorders in students, they usually undergo a wide-variety of clinical examinations & tests [1, 2], which further impacts their inclination towards learning, thus causing a cascaded learning-rejection effect in their mindset. To overcome this issue, researchers have developed interactive models that can gamify the process of LD estimation. Design of these models is a multidomain task, and requires development of efficient methods [3] for data collection, data presentation, student input capture, student behaviour capture, feature extraction from the captured data, classification & post-processing.

There are some research works which use informal methods for detection of LD. The methods used in these research works to diagnose LD in children depend on the provided checklists which contains the symptoms/signs of the respective learning disabilities. Many times the student himself is not aware that a particular symptom mentioned in the checklist is applicable to him. Sometimes the students are reluctant or hesitant to accept that they possess one or more symptoms specified in the checklist. Moreover, the list of symptoms is static and may not include many other symptoms of the various learning disabilities. Considering the above challenges, we need a system that can understand the learning process of the learner and detect the LD. It could further help in improving the learning. The system should be able to analyze the symptoms of LD, establish interrelationships between them and diagnose the presence of a learning disability. Once the disability is diagnosed the student will be able to learn according to his/her learning requirements/preferences that may lead to positive performance of the LD learner.

This paper aims at creating a learner model such that the detection of a particular type of learning disability is identified Each input set of behavioural patterns are categorized into LD & non-LD classes. Results of this model are processed via a feedback-based learning layer to cater to this particular type of learning disability. The system aims at reaching a class of children providing ease of accessing this system without any knowledge of other computer technologies. Our proposed LD estimation model uses primary features including, responses to analytical queries ($R_q$), time needed to solve these queries ($T_q$), unanswered queries ($U_q$), etc. Based on these primary features, various secondary features are extracted, which include but are not limited to, number of skipped questions ($Q_s$), probability of skipping ($P_s$), questions answered without reading ($Q_{wr}$), number of options selected before final answer ($N_{sel}$), etc. For instance, $P_s$ can be estimated via equation 1, while $Q_{wr}$ can be estimated via equation 2, which assists clinical experts to understand student behaviour before providing them with proper treatments.

$$P_{s_i} = \sum_{j=1}^{N_p} \frac{Q_{s_{i,j}}}{N_p} \tag{1}$$

$$Q_{wr} = \sum \bigcup_{j=1}^{N_p} T_j < \sum_{l=1}^{N_p} T_l * \frac{S_f}{N_p} \tag{2}$$

Where, $Q_{s_{i,j}}$ & $N_p$ represents number of questions of this category skipped previously, and number of questions previously attempted by the student, $T_j$ represents time needed to answer the question, while $S_f$ is a scaling factor, which is decided by the designer. These responses are collected for both LD & non-LD students, and a training dataset is generated, which is used to train a machine learning model. Design of such models is discussed in the next section of this text, where these models are evaluated in terms of their nuances, advantages, limitations & research gaps. Based on this discussion, it was observed that very few of these models are designed for end-to-end continuous learning support, and even fewer models are designed to improve capabilities of LD students, via methodological recommendations. Based on this observation, section 3 discusses design of a deep-learning model to improve learning capabilities of LD children via statistical modelling of examination behavioural patterns. The proposed method uses combination of various primary & secondary features, for training a custom 1D CNN Model, which is evaluated in section 4 in terms of accuracy of LD detection, average efficiency improvement for LD students, precision of LD detection, and average number of iterations needed by LD students to improve their performance. The performance was compared with various state-of-the-art models, and it was observed that the proposed model outperforms these models, which assists in its clinical deployment. Finally, this text concludes with some interesting observations about the proposed model, and recommends various methods to further improve its performance.

## 2. Literature Review

To improve learning capabilities of LD students, a wide variety of models are proposed by researchers. These models vary in terms of accuracy of learning improvement, speed of improvement, and other application-specific learning metrics. For instance, work in [4-6] proposes models that utilize Augmented Reality (AR), social &

collaborative technologies, and modification of learning environments. But these models are not able to assist a large variety of students, because of their infrastructure and cost requirements. These models also require students to learn about technologies before using them, which further restricts their scalability performance. To overcome this limitation, work in [7] proposes use of attribute selection and ensembles of different multimodal data sources, which are an environment independent approach, and can cater to a larger audience of students. Similar models are proposed in [8, 9, 10], wherein intervention-based approach, reading assistance (IRA), and use of optimum cost technologies for better scalability & reachability of performance improvement models. Extensions to these models are discussed in [11-13], wherein methods like special attention for LD students, inculcation of self-determination among students, and intervention-based models (IM) for continuous assistance are proposed. Out of these models the intervention model is highly efficient, because it assists in low-complexity, and high student throughput performance when applied in real-time scenarios. But these models are only aimed at improving the reading fluency related to dyslexia.

Models that provide memory-based improvements [14], machine learning-based methods for online learning [15], student directed techniques for in-classroom improvement [16], fostering of self-regulating capabilities in students via continuous motivation [17], and behavioural analysis [18] for multiple student types are also discussed. These methods allow for continuous performance improvement via recommendation of motivational & other behavioural enhancement at student-level, which assists in incremental improvement in student performance. Extensions to these models are discussed in [19-21], wherein researchers have discussed use of deep learning-based teaching (DLT), visual disability-based learning recommendations, and detection of issues on eLearning platforms. Based on design of these models' researchers can estimate lacunas in existing methods, and integrate deep learning to improve learning performance. Applications of such models are discussed in [22-24], wherein researchers have proposed use of Neuromuscular Control Training, conceptual Model for Games Design and Evaluation of Learning Games for Intellectual Disabled students. These models assist in deploying student-specific methods that can allow for improving overall student learning capabilities. Extensions to these models are proposed in [25, 26], where researchers have discussed use of context-aware augmentative & alternative communication system, and support vector Machines (SVM) for autism spectrum disorder (ASD) checks. But very few of these models are capable of considering real-time student behaviour, and recommend performance improvements depending upon their responses to LD-based questions. The methods used in these research works to diagnose LD in children depend on the provided checklists which contains the symptoms/signs of the respective learning disabilities

To overcome such limitations, section 4 proposes design of a deep-learning model which captures dynamic learning characteristics, to improve learning capabilities of LD children via statistical modelling of examination behavioural patterns. The proposed model was also evaluated w.r.t. various real-time scenarios, and compared with exiting methods to validate its performance. Section 3 discusses the methodology of research to achieve the objectives.

## 3. Methodology of Research

The research aims to develop a system for identifying the learning profile of a learning disabled with or without detection of LD. A behavioral analysis engine is built to analyze the learning behavior of the learning disabled. While a person is learning, the engine will try to capture the learning behavior of the learner through the attempt to identify his/her preference. A learner model will be built to include all this information about the learner. The analytics engine will update the learner model dynamically throughout the learning process of the learner. The model would be trained using deep learning to detect the learning disability on being provided the characteristics and features from the learning pattern of the learner.

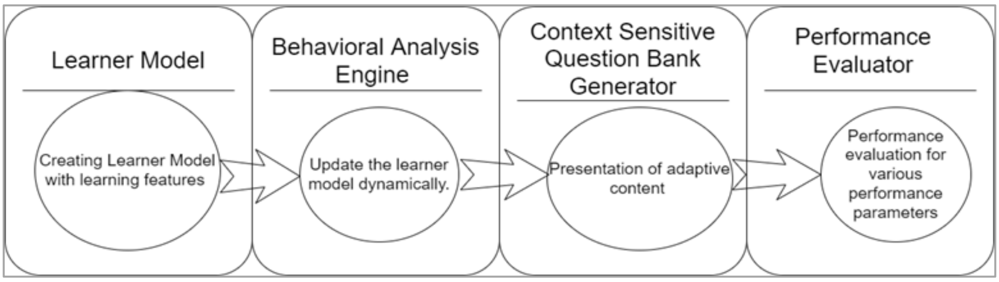


Fig. 1. Methodology of the research

A shown in fig. 1, the research methodology comprises the following task

1. Creating a learner model based upon the dynamic learning characteristics. This is done using the 1-D CNN model to classify the students as LD/NonLD.
2. This model will be updated for the changing learning behavior of the learner by the Behavioral Analysis Engine. This process is done throughout the learning process of the learner.

3. This engine will present the adaptive content to the learner, gather his/her performance and revise the model accordingly. The learner model will have the updated profile of the learner.
4. Based upon the response to the questions, the performance evaluator will evaluate the performance according to the various performance parameters.

## 4. Proposed Deep-Learning Model to Improve Learning Capabilities of LD Children via Statistical Modelling of Examination Behavioral Patterns

Based on the literature review, it can be observed that a wide variety of models are available for identification of LD in children, and most of them recommend methods to incrementally improve their performance. But a very few of these models are designed for end-to-end continuous learning support, which limits their applicability. Moreover, even fewer system models are designed to improve capabilities of LD students, via modification of system's internal parameters. To overcome these issues, this section proposes design of a novel deep-learning model that assists in improving learning capabilities of LD children via statistical modelling of examination behavioural patterns. The model initially proposes design of a novel dynamic questioning method which generates exam-questions depending upon previous responses of the student. Responses to these questions are collected via a Gamification approach, which encourages students to answer as many questions as possible. Responses to these answers are recorded for training set students, and features including question skipping probability, percentage of correct answers, question revisit probability, time spent on each question, un-attempted questions, & frequently skipped question types are evaluated via temporal pattern analysis. These responses are extracted from 12 different question types which include Basic Medium & Advanced English Grammar, direct, inference & vocabulary comprehension, sequencing, spelling, synonyms, Mathematics (addition & subtraction), and finding odd Man out. Based on classification results of this model, incremental recommendations are made for students, which assist them in concentrating on particular category of questions. Overall flow of the proposed model is depicted in fig. 2, wherein Master question data bank, and its context-sensitive processing layers can be observed. The model design in divided into different sub models, and each of these are described in separate sub-sections of this text. Researchers can implement these models in part(s) or as a whole, depending upon their application's requirements. It can be observed that design of behavioural analysis & VGGNet layers is described before context sensitive question bank Generation layer, because the later requires temporal student-level responses to modify its operations.

### *4.1. Design of the behavioural analysis layer*

This layer obtains questions from the Question Bank Generator (QBG) layer, and is used for estimation of student-level behaviour, which is evaluated & updated on a per-question basis. To perform this task, a wide variety of parameters are extracted. These parameters are divided into primary & secondary, and assist in estimation of temporal behaviour patterns. The primary parameters include,

- Number of questions correctly answered ($N_{QC}$)
- Number of questions incorrectly answered ($N_{QI}$)
- Number of questions not answered ($N_{NA}$)
- Number of skips ($N_{skips}$)
- Number of revisits ($N_{revisit}$)
- Timestamp at which question was presented to the student ($T_{present}$)
- Timestamp at which question was skipped by the student ($T_{skip}$)

Based on these primary parameters, the following secondary parameters are evaluated,

- Average delay needed to answer the question ($D_A$), which is estimated via equation 3

$$D_A = \frac{\sum_{i=1}^{N_{revisits_Q}} T_{skip_{i,Q}} - T_{present_{i,Q}}}{N_{revisits_Q}} \tag{3}$$

Where, $N_{revisits_Q}$ represents number of revisits for the given question ($Q$)

- Average number of skips for particular question type ($A_s$), which is estimated via equation 4,

$$A_s = \frac{\sum_{i=1}^{N_Q} N_{skips_i}}{N_Q} \tag{4}$$

Where, $N_{skips_i}$ represents number of skips for the particular question type, & $N_Q$ represents number of questions presented during examination of student.

- Probability of skipping a question ($P_{skip}$), is evaluated via equation 5,

$$P_{skip} = \sum_{i=1}^{N_Q} \frac{N_{skip_i}}{N_Q} \tag{5}$$

Where, $N_{skip}$ represents number of times student has skipped this particular question type. All these features are combined to form a behavioural feature vector (BFV), and tagged with student's LD status. The tagged dataset is given to a customized 1D VGGNet based CNN model, which assists in high-density feature augmentation & classification, and is discussed in the next section of this text.

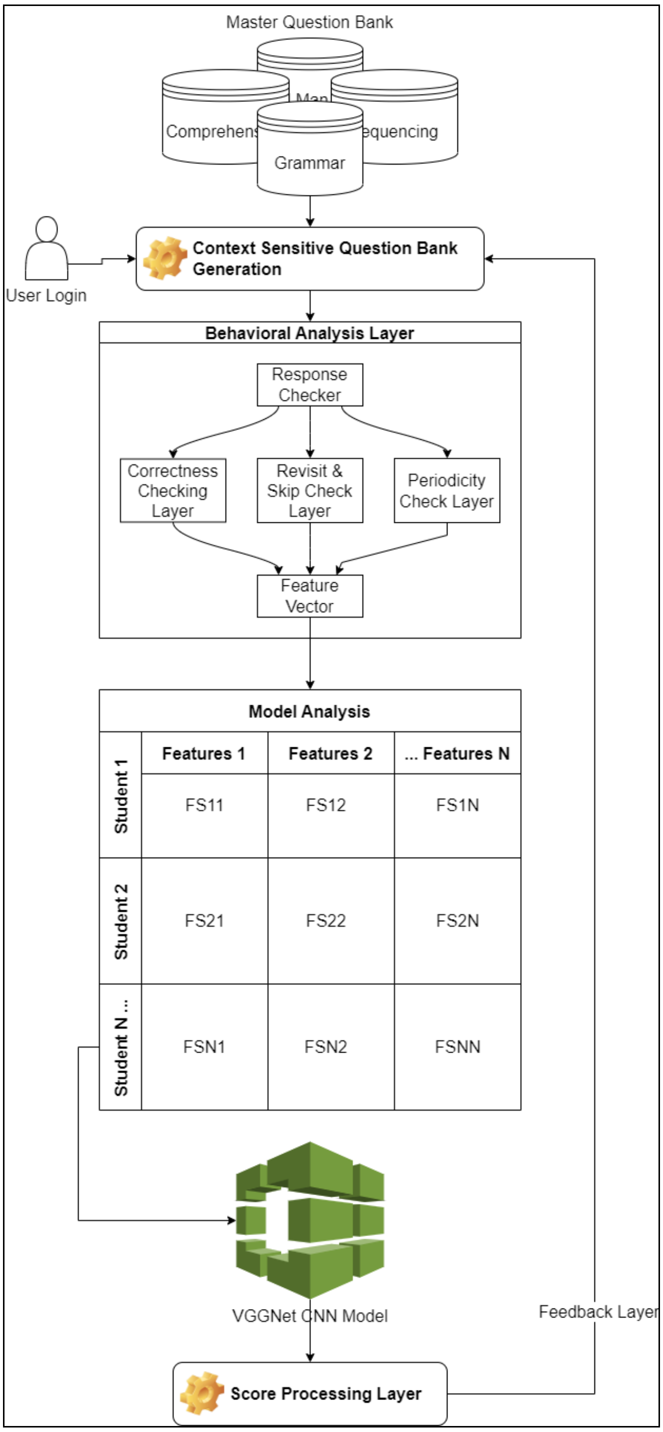


Fig. 2. Overall flow of the proposed model

### 4.2. Design of the VGGNet based CNN Model

After extraction of behavioural feature patterns, a customized VGGNet based CNN Model is used, which assists in low error categorization of features into LD & non-LD classes. Design of this model is depicted in fig. 3, wherein its internal layer structure can be observed.

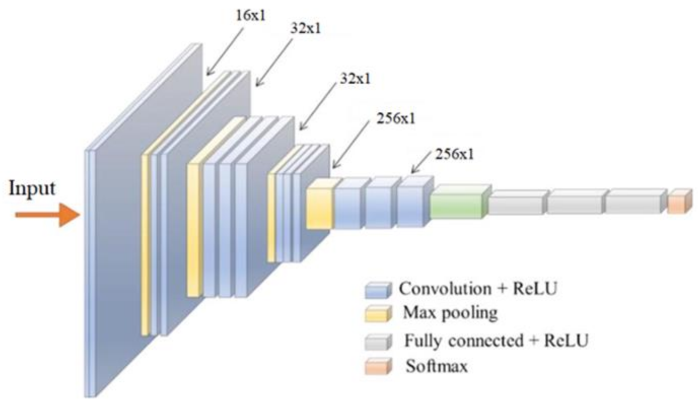


Fig. 3. Internal structure of the deep learning model

From the model design it can be observed that all 16 behavioural patterns are input to the system, and a series of convolutional layers are used to process them. Each of these layers extracts a wide variety of dense features from the behavioural patterns, which assists in high-density feature augmentations. These output features are evaluated via equation 6, wherein a leaky rectilinear unit (LReLU) is used for feature activation & control,

$$Conv_{out_i} = \sum_{a=-\frac{m}{2}}^{\frac{m}{2}} B_{feat}(i-a) * ReLU\left(\frac{m}{2}+a\right) \tag{6}$$

Where, $B_{feat}$ represents behavioural features, while $m, a$ represents window size & padding size for the convolutional layer. Due to multiple stride sizes, the layer is capable of extracting a large number of features, which introduces redundancy in the extracted feature sets. To reduce this redundancy, Max Pooling of features is performed, wherein features with maximum variance are extracted, while others are discarded from the feature set. To perform this task, a variance threshold is estimated via equation 7 as follows,

$$var_t = \left(\frac{1}{N_f} * \sum_{x \in N_f} \frac{var(x)}{S_f}\right)^{\log(var(x))} \tag{7}$$

Where, $N_f, var(x), \& S_f$ represents number of extracted features, variance of the feature vector, and similarity of the feature vector with other features. Variance is estimated via equation 8,

$$var(x) = \sqrt{\sum_{i=1}^{N} \frac{\left[x_i - \sum_{j=1}^{N} \frac{x_j}{N}\right]^2}{N-1}} \tag{8}$$

Where, $N$ represents number of convolutional features extracted by this layer. Similarly, the value of $S_f$ is evaluated via equation 9 as follows,

$$S_f = \frac{\sum_{j=1}^{N} \frac{\sum_{i=1}^{N} x_i * x_j}{\sqrt{\sum_{i=1}^{N} x_i^2 * x_j}}}{N} \tag{9}$$

The model varies window sizes in the range 16x1, 32x1, 256x1, and 512x1 in order to extract a large number of feature sets. Each of these layers is used to extract $N$ features per stride from the behavioural patterns. The stride is moved via a 5x1 window for effective feature extraction & control. The extracted features are given to a fully connected neural network (FCNN) that can classify extracted behavioural patterns into LD & non-LD classes. The designed network uses a SoftMax activation function in order to perform backpropagation-based training, which is controlled via equation 10 as follows,

$$c_{out} = SoftMax\left(\sum_{i=1}^{N_f} f_i * w_i + b\right) \tag{10}$$

Where, $f_i$ represents extracted behavioural feature vectors, $w_i$ represents weight of each feature, which is tuned by the Neural Network, $b$ represents a bias value, and $N_f$ represents number of features extracted by the convolutional layer respectively. Based on this classification, each input set of behavioural patterns are categorized into LD & non-LD classes. Results of this model are processed via a feedback-based learning layer, which is described in the next sub-section of this text.

*4.3. Design of feedback layer with context sensitive question bank Generator*

Both LD & non-LD students are evaluated for multiple examinations, and their responses are recorded. These responses are stored for each subject type, and an average differential score per-subject is evaluated via equation 11 as follows,

$$ADS_{Student}(Sub) = \frac{\sqrt{\left(\sum_{i=1}^{N_{eval}}\left[C_{score_i} - \sum_{j=1}^{N_{eval}} C_{score_j}\right]^2\right)}}{N_{eval}} \tag{11}$$

Where, $C_{score}$ represents correctness score for the given question type, and is evaluated via equation 12 as follows,

$$C_{score_i} = \frac{N_{QC_i}}{N_{QC_i} + N_{QI_i} + N_{NA_i}} \tag{12}$$

Based on this score for LD & non-LD students, an incremental score is evaluated for each subject via equation 13 as follows,

$$I_{score}(Sub)_i = \frac{ADS_{NLD}(Sub) - ADS_{LD}(Sub)_i}{ADS_{NLD}(Sub)} \tag{13}$$

Where, $ADS_{LD}$ & $ADS_{NLD}$ represents average differential score for LD & Non-LD Students, and is evaluated at student level $(i)$ for each LD student. This assists in estimation of average performance deviation for LD students when compared with their normal counterparts. To evaluate number of questions per subject, a probability score at subject-level is initialized via equation 14,

$$P_s(Sub) = \frac{1}{N_{sub}} \tag{14}$$

Where, $N_{sub}$ represents number of subjects for which this model is being deployed, and $P_s$ represents probability score for that subject. This score is modified via intensity & polarity of incremental score. To perform this modification, the following conditions are evaluated,

- If $I_{score} \le 0$, this indicates that non-LD students are performing at-par with LD students for the given subject, and do not need any additional evaluation, thus, subject probability score is modified via equation 15,

$$New\big(P_s(Sub)\big) = P_s(Sub) - \frac{|I_{score}|}{N_{sub} * Max\left(\bigcup_{i=1}^{N_{sub}} I_{score}\right)} \tag{15}$$

- If $I_{score} > 0$, then it indicates that student needs to improve their performance for the given subject, thus subject level probability score is modified via equation 16 as follows,

$$New\big(P_s(Sub)\big) = P_s(Sub) + \frac{2 * |I_{score}|}{N_{sub} * Max\left(\bigcup_{i=1}^{N_{sub}} I_{score}\right)} \tag{16}$$

Based on this new value of subject level probability, number of questions for each subject are evaluated via equation 17,

$$N_q(Sub) = \frac{P_S(Sub)}{\sum_{i=1}^{N_{sub}} P_S(i)} * T_q \tag{17}$$

Where, $T_q$ represents total number of questions to be attempted by the student, and are decided by the system designer. Priority with which these questions are shown to the student is decided by the subject-level priority factor, which is evaluated via equation 18,

$$P_{fact}(Sub) = Median[Shown(Sub) \cap All(Sub)] \tag{18}$$

Where, $Shown(Sub)$ & $All(Sub)$ represents set of questions shown to the student, and set of all questions randomly generated by the examination model. Once a question type is shown to the student, then it is added to the $Shown(Sub)$ set of questions. Based on this process, question sets are generated, their responses are recorded, and using these responses behaviour of students is evaluated for dynamic question bank generation & control. Once a student has completed an iteration of examination, then the system recommends improvement areas. These improvement recommendations are used for continuous performance enhancement of the student for a particular subject. To provide these recommendations, all subjects with negative incremental scores are identified, and an improvement percentage is evaluated via equation 19, wherein differential score average for LD & non-LD students is used,

$$Imp(Sub)_i = \frac{I_{score}(Sub)_i * \sum_{j=1}^{N_{NLD}} ADS_j(Sub)}{\sum_{j=1}^{N_{NLD}} ADS_j(Sub) + \sum_{l=1}^{N_{LD}} ADS_l(Sub)} \tag{19}$$

This improvement score in percentage is recommended to the student at subject-level, and assists them in identification of improvement areas. Based on these recommendations, various LD students, and their performance was evaluated. This performance was compared with various state-of-the-art models in terms of percentage of questions covered, precision of answering, accuracy of answering, delay needed to answer a question, and percentage of questions skipped, in the next section of this text.

## 5. Results Analysis and Comparison

The proposed model uses a combination of behaviour analysis, student categorization & performance recommendation in order to improve learning capabilities of LD students. Performance of this model was evaluated via manual data collection for 80+ LD students, analysing their responses, and comparing them with non-LD students. This performance was evaluated in terms of percentage of questions covered (PQC), precision of answering (PA), accuracy of answering (AA), delay needed to answer a question (DA), & percentage of questions skipped (PQS), and compared with AR [4], IM [13], and DLT [19] models. Question bank of over 150 LD specific questions, was generated manually via referring various state-of-the-art models, and can be obtained by contacting the authors. Each of these evaluations were done over 8 different examinations for 80 students, and respective metrics were averaged & tabulated in this section for performance check. Out of 640 evaluations, 70% were used for training the model, and 100% were used for testing & validation purposes. The reason for this overlap in dataset is to estimate its blind & non-blind performance. For instance, the percentage of questions covered (PQC) which represents average percentage of questions which were attempted by students across multiple evaluations, can be observed from table 1 as follows,

Table 1. PQC Evaluation for different models

| Number of evaluations | PQC (%) AR [4] | PQC (%) IM [13] | PQC (%) DLT [19] | PQC (%) DL2 CSM BP |
|---|---|---|---|---|
| 50 | 65.30 | 61.50 | 66.74 | 77.69 |
| 75 | 65.80 | 61.90 | 67.21 | 78.21 |
| 100 | 66.20 | 62.30 | 67.63 | 78.67 |
| 125 | 66.40 | 62.80 | 68.00 | 79.22 |
| 150 | 66.80 | 63.50 | 68.58 | 79.70 |
| 200 | 67.20 | 63.60 | 68.84 | 80.04 |
| 250 | 67.30 | 64.10 | 69.16 | 80.28 |
| 300 | 67.40 | 64.20 | 69.26 | 80.47 |
| 350 | 67.50 | 64.50 | 69.47 | 81.32 |
| 400 | 67.60 | 66.80 | 70.74 | 81.83 |
| 425 | 67.50 | 66.17 | 70.35 | 81.81 |
| 500 | 67.70 | 66.65 | 70.71 | 82.23 |
| 525 | 67.90 | 67.13 | 71.07 | 82.68 |
| 550 | 68.20 | 67.61 | 71.48 | 83.09 |
| 575 | 68.30 | 68.09 | 71.79 | 83.45 |
| 600 | 68.40 | 68.57 | 72.09 | 83.80 |
| 620 | 68.50 | 69.05 | 72.40 | 84.22 |
| 640 | 68.80 | 69.54 | 72.81 | 84.66 |

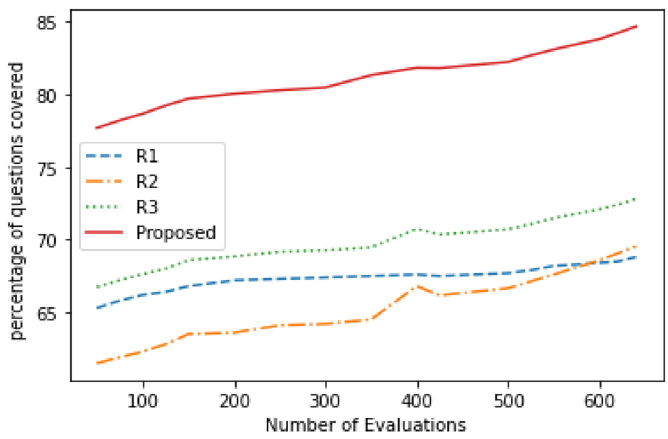


Fig. 4. PQC Evaluation for different models

Based on this evaluation, and fig. 4, it can be observed that the proposed model is 15.4% better than AR [4], 14.6% better than IM [13], and 10.5% better than DLT [19] for multiple evaluations. The reason for this improvement is use of priority-based question Generation, which assists students to answer questions based on their strengths. This motivates students to answer as many questions as possible, because they get a sense of satisfaction by initially answering moderate level questions, and then alternatively answering easier and difficult question types. Similarly, observations were made for precision of answering (PA), and can be observed from table 2 as follows,

Table 2. PA Evaluation for different models

| Number of evaluations | PA (%) AR [4] | PA (%) IM [13] | PA (%) DLT [19] | PA (%) DL2 CSM BP |
|---|---|---|---|---|
| 50 | 70.44 | 71.24 | 80.24 | 83.71 |
| 75 | 70.94 | 71.73 | 80.79 | 84.30 |
| 100 | 71.39 | 72.18 | 81.28 | 84.81 |
| 125 | 71.78 | 72.67 | 81.79 | 85.31 |
| 150 | 72.39 | 73.38 | 82.38 | 85.98 |
| 200 | 72.67 | 73.58 | 82.71 | 86.32 |
| 250 | 73.00 | 74.03 | 83.02 | 86.68 |
| 300 | 73.11 | 74.15 | 83.18 | 86.83 |
| 350 | 73.33 | 74.43 | 83.78 | 87.28 |
| 400 | 74.67 | 76.41 | 84.76 | 88.57 |
| 425 | 74.26 | 75.84 | 84.54 | 88.22 |
| 500 | 74.64 | 76.31 | 84.97 | 88.67 |
| 525 | 75.02 | 76.78 | 85.41 | 89.13 |
| 550 | 75.45 | 77.27 | 85.87 | 89.62 |
| 575 | 75.77 | 77.71 | 86.24 | 90.01 |
| 600 | 76.10 | 78.15 | 86.61 | 90.39 |
| 620 | 76.42 | 78.58 | 87.01 | 90.79 |
| 640 | 76.85 | 79.08 | 87.48 | 91.30 |

Based on this evaluation, and fig. 5, it can be observed that the proposed model is 12.9% better than AR [4], 8.5% better than IM [13], and 3.2% better than DLT [19] for PA performance under multiple evaluations. The reason for this improvement is use of behavioural learning & recommendations to students based on the difficulty faced in a particular lesson. Recommendations provided help the students to focus on subjects requiring remediation in the form of more questions of the lesson. Similarly, observations were made for accuracy of answering (AA), and can be observed from table 3 as follows,

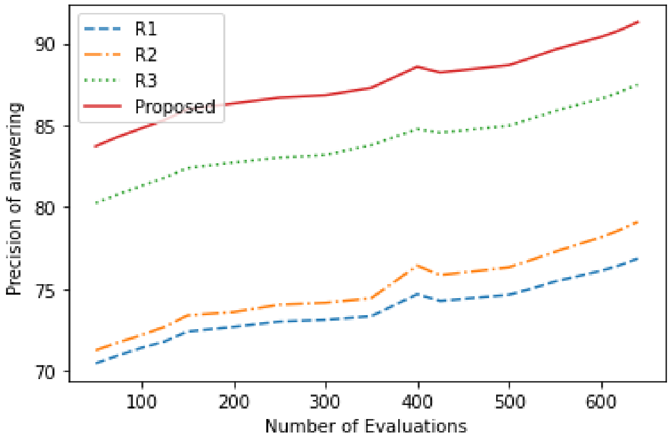


Fig. 5. PA Evaluation for different models

Table 3. Accuracy of Answering for different models

| Number of evaluations | AA (%) AR [4] | AA (%) IM [13] | AA (%) DLT [19] | AA (%) DL2 CSM BP |
|---|---|---|---|---|
| 50 | 67.87 | 68.07 | 69.99 | 82.77 |
| 75 | 68.37 | 68.53 | 70.48 | 83.34 |
| 100 | 68.79 | 68.97 | 70.91 | 83.84 |
| 125 | 69.09 | 69.47 | 71.33 | 84.37 |
| 150 | 69.59 | 70.19 | 71.88 | 84.97 |
| 200 | 69.93 | 70.35 | 72.17 | 85.31 |
| 250 | 70.15 | 70.84 | 72.47 | 85.62 |
| 300 | 70.26 | 70.95 | 72.59 | 85.79 |
| 350 | 70.42 | 71.25 | 72.98 | 86.46 |
| 400 | 71.13 | 73.44 | 74.05 | 87.39 |
| 425 | 70.88 | 72.83 | 73.76 | 87.20 |
| 500 | 71.17 | 73.31 | 74.13 | 87.64 |
| 525 | 71.46 | 73.80 | 74.52 | 88.11 |
| 550 | 71.83 | 74.30 | 74.93 | 88.57 |
| 575 | 72.04 | 74.77 | 75.25 | 88.95 |
| 600 | 72.25 | 75.24 | 75.57 | 89.33 |
| 620 | 72.46 | 75.71 | 75.91 | 89.75 |
| 640 | 72.83 | 76.21 | 76.33 | 90.23 |

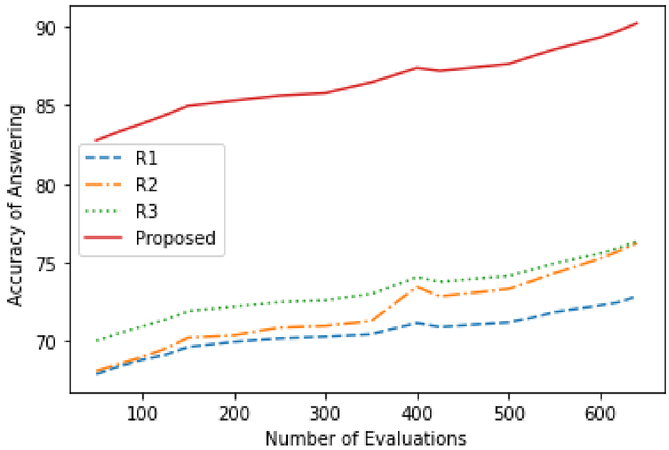


Fig. 6. Accuracy of Answering for different models

Based on this evaluation, and fig. 6, it can be observed that the proposed model is 14.3% better than AR [4], 9.5% better than IM [13], and 9.4% better than DLT [19] for AA performance under multiple evaluations. The reason for this improvement is use of behavioural learning & subject-level recommendations to students according to the difficulty detected which further enables the students to answer questions based on their preferences. Similarly, observations were made for delay needed to answer a question (DA), and can be observed from table 4 as follows,

Table 4. DA Evaluation for different models

| Number of evaluations | DA (s) AR [4] | DA (s) IM [13] | DA (s) DLT [19] | DA (s) DL2 CSM BP |
|---|---|---|---|---|
| 50 | 13.57 | 13.39 | 14.46 | 8.14 |
| 75 | 13.67 | 13.48 | 14.56 | 8.19 |
| 100 | 13.76 | 13.56 | 14.65 | 8.24 |
| 125 | 13.82 | 13.66 | 14.74 | 8.30 |
| 150 | 13.92 | 13.80 | 14.86 | 8.36 |
| 200 | 13.99 | 13.84 | 14.91 | 8.39 |
| 250 | 14.03 | 13.93 | 14.98 | 8.42 |
| 300 | 14.05 | 13.95 | 15.00 | 8.44 |
| 350 | 14.08 | 14.01 | 15.08 | 8.50 |
| 400 | 14.23 | 14.45 | 15.30 | 8.59 |
| 425 | 14.18 | 14.32 | 15.24 | 8.57 |
| 500 | 14.23 | 14.42 | 15.32 | 8.62 |
| 525 | 14.29 | 14.51 | 15.40 | 8.66 |
| 550 | 14.37 | 14.61 | 15.49 | 8.71 |
| 575 | 14.41 | 14.70 | 15.55 | 8.75 |
| 600 | 14.45 | 14.80 | 15.62 | 8.78 |
| 620 | 14.49 | 14.89 | 15.69 | 8.83 |
| 640 | 14.57 | 14.99 | 15.77 | 8.87 |

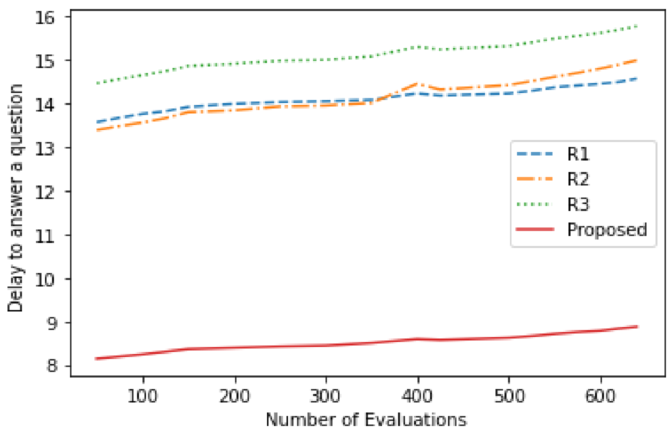


Fig. 7. DA Evaluation for different models

Based on this evaluation, and fig. 7, it can be observed that the proposed model is 35.8% better than AR [4], 37.2% better than IM [13], and 40.3% better than DLT [19] for multiple evaluations. The reason for this improvement is use of priority-based question Generation & use of behavioural learning, which assists students to answer questions with better speed. Similarly, observations were made for percentage of questions skipped (PQS), and can be observed from table 5 as follows,

Table 5. PQS Evaluation for different models

| Number of evaluations | PQS (%) AR [4] | PQS (%) IM [13] | PQS (%) DLT [19] | PQS (%) DL2 CSM BP |
|---|---|---|---|---|
| 50 | 18.55 | 19.67 | 13.22 | 10.29 |
| 75 | 17.95 | 19.14 | 12.61 | 9.94 |
| 100 | 17.45 | 18.62 | 12.07 | 9.63 |
| 125 | 17.09 | 18.03 | 11.55 | 9.33 |
| 150 | 16.49 | 17.17 | 10.86 | 8.90 |
| 200 | 16.08 | 16.99 | 10.51 | 8.72 |
| 250 | 15.82 | 16.41 | 10.14 | 8.47 |
| 300 | 15.69 | 16.28 | 9.98 | 8.39 |
| 350 | 15.50 | 15.93 | 9.51 | 8.19 |
| 400 | 14.64 | 13.34 | 8.18 | 7.23 |
| 425 | 14.94 | 14.07 | 8.54 | 7.51 |
| 500 | 14.60 | 13.49 | 8.08 | 7.23 |
| 525 | 14.25 | 12.92 | 7.60 | 6.95 |
| 550 | 13.81 | 12.33 | 7.09 | 6.64 |
| 575 | 13.56 | 11.77 | 6.69 | 6.40 |
| 600 | 13.30 | 11.22 | 6.29 | 6.16 |
| 620 | 13.05 | 10.66 | 5.87 | 5.92 |
| 640 | 12.61 | 10.07 | 5.35 | 5.61 |

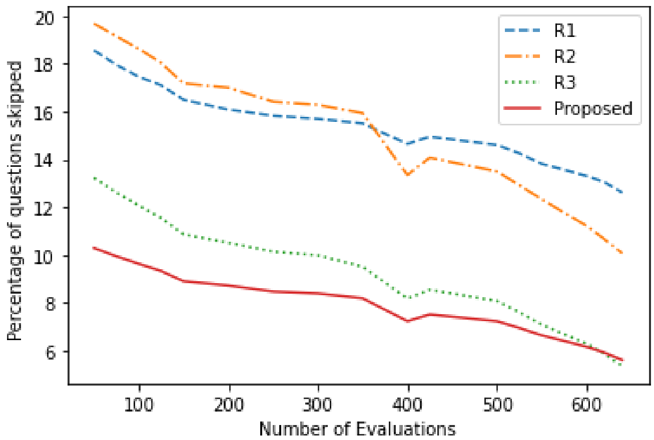


Fig. 8. PQS Evaluation for different models

Based on this evaluation, and fig. 8, it can be observed that the proposed model is 6.5% better than AR [4], 4.6% better than IM [13], and at par with DLT [19] for PQS performance under multiple evaluations. The reason for this improvement is use of behavioural learning & subject-level recommendations to students, along with priority-based question Generation, which assists students to skip fewer questions. Thus, it can be observed that the proposed model is capable of improving performance of LD students, which makes it highly useful for deployment under a wide variety of real-time application & clinical scenarios. The acuuracy and reliability of the results are ensured because the dataset is not a synthetic dataset but generated from genuine responses by LD and nonLD students.

## 6. Conclusion and Future Scope

The deep-learning model (DL2CSMBP) assists the LD children in improving their learning capacities by statistically modelling their test behavior patterns. The students attempt 12 different question types including English Grammar (Basic, Medium, Advanced), Comprehension (with direct, inference and vocabulary questions annotated), Sequencing, Spelling, Word Meanings, Mathematics (addition & subtraction), and finding the odd Man out. The student responses are processed using a deep learning model that extracts statistical characteristics from recorded data. These traits include the probability that a question will be skipped, the number of correct responses, the number of revisits, the amount of time spent on each question, the probability that a question will go unattempt, and the types of questions that are frequently skipped. The proposed DL2CSMBP model uses a combination of deep learning classifiers with behavioural pattern analysis models for incrementally improving performance of LD students. This performance is improved majorly due to use of subject-specific recommendations, which assists students to identify areas that require more focus & effort. The engine uses a combination of psychologically intelligent decision units for question bank Generation, and prioritization, which assists in Gamification of questions at a per-student & per-subject basis. Due to use of these methods, the proposed model is able to achieve 84.6% performance in terms of percentage of questions covered, which is 15.4% better than AR [4], 14.6% better than IM [13], and 10.5% better than DLT [19] for multiple evaluations. Similarly, the model is able to achieve over 90% precision & accuracy performance for answering questions, which is nearly 14.3% better than AR [4], 9.5% better than IM [13], and 9.4% better than DLT [19] under multiple evaluations. Due to use of dynamic question bank Generation, the model is able to incline students towards solving the questions faster, because of which, the model showcases 35.8% faster response than AR [4], 37.2% faster response than IM [13], and 40.3% faster response than DLT [19] for multiple evaluations. This performance is backed up by a reduction in percentage of questions skipped (PQS), which indicates that students are willing to answer a greater number of questions. This assists in improving the quantity & quality of data collection, thus improving usability of the model w.r.t. number of student evaluations. Due to these enhancements, the model is capable of deployment under a wide variety of clinical & non-clinical application scenarios. In future, researchers can validate model's performance on their specialized datasets, which will assist in estimating any lacunas in current model implementation. Furthermore, researchers can utilize bioinspired & Q-Learning models for better feature augmentation, which might incrementally improve model performance under different application scenarios.

## Declarations Section

**Ethical Approval and Consent to participate**:

The dataset involves children of grade 6,7, and 8 who have attempted the lessons online though an e-learning application. On the home page of the application, a request application on the institute letterhead is uploaded whereby the author seeks consent to participate.

**Consent for publication**:

On the home page of the application, a request application on the institute letterhead is uploaded whereby the author seeks consent of the participants.

**Availability of supporting data**:

The dataset can be provided on request.

**Competing interests: None**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Authors' Profiles

**Masooda Modak** has received M.E. (Information Technology) degree from Mumbai University in 2015, pursuing Ph.D. from Mumbai University, INDIA. She has more than 15 years of experience in teaching. Currently she is working as Assistant Professor in Computer Engineering Department at South Indian Graduate School of Technology, Mumbai. Her areas of interest are Learning Analytic, Data Mining, Machine Learning. She has completed 3 minor research projects for Mumbai University. She is a Life member of ISTE.

**Prachi Gharpure** has completed her master's in computer engineering From VJTI and Ph.D. in Technology from SNDT. She has over 3 decades of experience in Teaching and Academic Administration During her career path, she has grown to take up the Leadership position of heading the institution. Dr. Prachi's area of interest are Computer Programming, Computer Organization, Object Oriented Analysis and Design, Project Management, Electronic Communication, Digital Electronics and Software Engineering. Her areas of research are E-learning & Software Engineering. She has numerous National & International Publications and Research. Dr. Prachi has also won accolades and awards to her credit, recent one being Higher Education Forum Award for Contribution to Information Technology. She is a Chairman of BOS (Computer) at Mumbai University, Member of Syllabus Committee and Staff selection committee for Maharashtra State, Convener of several Mumbai University Committees related to affiliation, approvals & fact findings.

**Sasikumar M** is currently Director of CDAC Mumbai. He has been with CDAC since 1987 after completing his BTech from IIT Madras. He completed his Post-graduation from IISc, Bangalore and Doctorate from BITS, Pilani. His areas of interest are Artificial Intelligence, and Educational Technology. He has co-authored two books, one is with Prentice Hall on Parallel Computing. 6 students have completed their PhD under his guidance and three are in progress. He has initiated and nurtured a number of projects in the area of AI and E-learning during his career. He has over 100 publications so far. He is programme committee member in a number of international conferences, member of Board of Studies and advisory board for select institutions.

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