

## DIGITAL SCREENING OF SPECIFIC LEARNING DISABILITIES IN CHILDREN

Jay.R.Dhadke<sup>1</sup>, Sonali Patil<sup>2</sup>, Rohit Shinde<sup>3</sup>, Anurag Ghosh<sup>4</sup>, Aditi Pawar<sup>5</sup>, Krishang Parakh<sup>6</sup>

Received : 02/06/2023  
Received in revised form : 15/07/2023  
Accepted : 30/07/2023

**Keywords:**  
Children, Neurodevelopmental Disorders, Specific Learning Disabilities, Dyslexia, Screening, Mobile App, Cross-platform Application, Flutter.

Corresponding Author:  
**Dr. Sonali Patil**,  
Email: sonalipatil@somaiya.edu.

DOI: 10.47009/jamp.2023.5.4.246

Source of Support: Nil,  
Conflict of Interest: None declared

*Int J Acad Med Pharm*  
2023; 5(4); 1220-1226



<sup>1</sup>Postgraduate Medical Officer (PGMO), Department of Paediatrics, Pandit Madan Mohan Malviya Shatabdi Municipal Hospital, Govandi, Mumbai India.

<sup>2</sup>Professor, Department of Information Technology, KJ Somaiya College of Engineering, Mumbai India.

<sup>3,4,5,6</sup>Final year student, B.Tech, Department of Information Technology, KJ Somaiya College of Engineering, Mumbai India.

### Abstract

**Background:** Specific Learning Disabilities (SLDs) are prevalent neurodevelopmental disorders affecting children worldwide, impacting their academic progress and social well-being. Early identification and intervention are crucial to improving outcomes for affected individuals. Early identification of SLDs is essential to mitigate their adverse impact on academic performance and social development. **Materials and Methods:** The present study was conducted in Mumbai with the data collected manually from parents, students, psychiatrists, and school counselors across Mumbai city via surveys and interviews hence forming a diversified dataset for accurate and in-depth analysis for our application. While keeping the dataset extensive in terms of region and the targeted age group restricted to 8-12 years as the primary focus in the early detection of SLD, the study was conducted. In this study, we have designed a mobile app using Flutter, a versatile framework for building cross-platform applications, to screen children for SLDs through a series of questionnaires. **Results:** The data collected involved 50 real records, augmented to 400 records. The training accuracy was obtained to be 95% percent thus giving an accurate representation of the chances of a particular child having a SLD also with the possible probabilities of 4 different categories of SLD.

## INTRODUCTION

Learning disability is a neurologically-based processing disorder resulting from “faulty” wiring in the cortex. Specific learning disability (SLD) is a condition where there is a deficit in processing language, spoken or written, that may manifest itself as a difficulty to comprehend, speak, read, write, spell, or to do mathematical calculations. SLDs encompass a range of specific difficulties, such as dyslexia (reading), dysgraphia (writing), dyscalculia (mathematics), and others. These conditions are distinct from other learning difficulties and are not solely attributed to external factors, such as lack of appropriate instruction or inadequate language proficiency. Learning disabilities are different for every individual. No two individuals can have the exact disability.

Children with SLDs often experience challenges in school and may exhibit difficulties in reading, writing, spelling, understanding mathematical concepts, and organizing information. Despite these difficulties, individuals with SLDs often possess

average or above-average intelligence in other areas. It is essential to identify SLDs early, as timely intervention can significantly improve academic and social outcomes for affected children.<sup>[1]</sup> Support and accommodations provided at an early stage can help individuals with SLDs to develop compensatory strategies and build on their strengths to succeed in their educational journey and beyond. Assessment for SLDs typically involves a comprehensive evaluation conducted by trained professionals, such as clinical psychologists, occupational therapists and educational specialists. The evaluation may include standardized tests, observations, interviews, and a review of the individual's developmental history. Once diagnosed, individuals with SLDs can receive specialized instruction and support tailored to their specific needs. It is crucial to adopt a multidisciplinary approach involving educators, parents, and mental health professionals to ensure a collaborative and holistic approach to supporting individuals with SLDs. By raising awareness and promoting understanding, society can create an inclusive environment that recognizes and

accommodates the unique challenges faced by individuals with specific learning disabilities. Therefore, the development of efficient and accessible screening tools becomes crucial to identify SLDs at an early stage.

In this context, mobile technology presents a promising avenue for SLD screening. With the widespread use of smartphones, developing a mobile app for SLD assessment can provide parents and teachers with a convenient and user-friendly tool for early detection.<sup>[1,4,5]</sup> Such an app can bridge the gap between caregivers and mental health professionals, ensuring timely access to appropriate resources and support.

## MATERIALS AND METHODS

The purpose of this project is to harness digital means for the assessment of reading and writing difficulties among people with specific learning disabilities and to develop a way to screen them as early as possible when the symptoms are relatively mild and easier to manage. The system is designed to be user-centric that will ensure that the user requirements conform to the required standards.

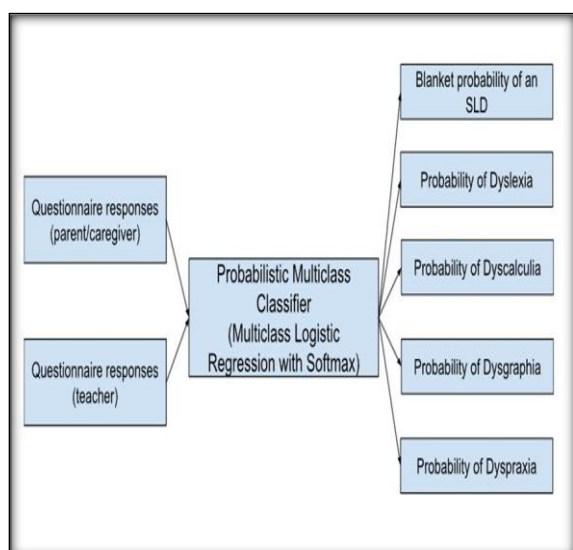
### Inclusion Criteria

As the study deals with the early screening of SLD in children, the study is only considered with children in the age group of 8 - 12 years old only.

### Exclusion Criteria

The children below 8 years of age are excluded due to the developmental variability, lack of developmental assessments for younger children and lack of other maturational factors such as attention, language and communication skills.<sup>[3]</sup> The age group of children above 12 years is also excluded as the study deals with early screening of SLD's.

The Level-0 Data Flow Diagram describing the screening process is illustrated in figure 1.



The overall study was based on the inputs of parents, teachers and primary caregivers of the children as screening is a clinical procedure that

involves taking inputs from the child under an occupational therapist or a child counselor. Hence, the app only deals with the preparation of a checklist, just to give an overall picture of the child's learning process, thus giving the susceptibility to a particular SLD, which can only be detected in older children by an expert of the field.

The study was conducted in different steps. The different steps are as followed:

### Checklist Development

The checklist is a concrete step in screening of SLD's. The checklist was prepared by the general guidelines of the National Center for Learning Disabilities. The study drew insights from various online resources and publicly available SLD checklists. The researchers compiled information from multiple sources to create 12 question categories for the parents' questionnaire and 11 categories for the teacher's questionnaire. Each question required a binary response (Yes or No), making the assessment process efficient. The questionnaires, comprising 65 questions for parents and 52 questions for teachers, aimed to identify potential SLDs in children aged 8-12.

The questionnaires were developed with inputs from professionals at Prafula - Center for Psychological Wellness, Andheri, and were further validated by Dr. Yogita Shendge and Ms. Shraddha Kamble of Peadofit - Advanced Child Development Centre, Chembur. This rigorous approach ensured the alignment of the questions with expert opinions and best practices.

### Data Collection

These checklists were administered by Peadofit at their clinic and a total of 30 responses were collected. We were also permitted to administer these checklists independently, and we managed to collect 20 responses. This brings our "real" responses count (number of records in the dataset) to 50.

### Data Augmentation

Since the dataset collected for this project contained only 50 data points, it was too small to train a machine-learning model. To address this issue, data augmentation techniques were employed to increase the number of records in the dataset. These techniques involved transformations that increased the diversity of the dataset while maintaining its relevance. This increased the dataset to 400 records, which was large enough to train the machine learning model.

### The details of our dataset are summarized below

- Total 400 records
- 50 records are real-life records of children, manually administered and approved by Peadofit in collaboration with us, using the checklists that we made. 350 are the artificially generated data points that were simulated in a logical and validated fashion.
- The dataset includes 117 attributes and a target variable making it a total of 118 attributes.

- The 117 attributes are the total responses of parents and teachers to the questions in the checklist with 65 questions for the parents and 52 questions for the teachers.
- All value types are binary. Yes being 1, and no being 0.
- Target variable can be 0, 1, 2, 3, or 4, where
  - 0 relates to Normal Child
  - 1 relates to Dyslexia
  - 2 relates to Dyscalculia
  - 3 relates to Dysgraphia
  - 4 relates to Dyspraxia

### Shortlisting the ML Model

For our application and particular use case, we needed a probabilistic multiclass classification model which can output 5 probabilities: a blanket probability of the existence of any SLD, a probability of dyslexia, a probability of dyscalculia, a probability of dysgraphia, and a probability of dyspraxia. Our selected model should also work fine with fewer records. The output layer of our classifier should have a sigmoid or SoftMax activation function to output the class-wise probabilities.

**Table 1: summarizes a preliminary study of 3 possible ML classifiers that we considered for the final shortlisting**

Model	Pros	Cons
Multiclass Logistic Regression with SoftMax	A simple and interpretable model can handle high-dimensional data, outputs probabilities for each class	Assumes linear relationship between input features and target variables, sensitive to outliers and irrelevant features, not suitable for non-linearly separable data
Multinomial Naive Bayes Classifier	The simple and efficient model can handle high-dimensional data and requires less training data compared to other models	Assumes independence between input features, may not work well with highly correlated features, can produce inaccurate probabilities if the class distributions are imbalanced
Random Forest Decision Tree (With SoftMax)	Non-parametric and flexible model, can handle high-dimensional data, can handle non-linearly separable data, can handle missing values and outliers, outputs probabilities for each class, can handle imbalanced data	Not as interpretable as logistic regression or Naive Bayes, can be prone to overfitting if the number of trees is too high, computationally more expensive than logistic regression or Naive Bayes

The results of the Multiclass Logistic Regression model with SoftMax AF, the Multinomial Naïve Bayes Classifier, and the Random Forest Decision Tree with SoftMax AF are shown in the figures below. A summary table is given after the figures which shows the performance statistics of each model.

Figure 2 shows confusion matrices (of accuracies) of the validation set, test set, and train set – for the Multiclass Logistic Regression Model with SoftMax. Confusion matrices show that Multiclass Logistic Regression with SoftMax is the best fit for our application based on our nature of data.

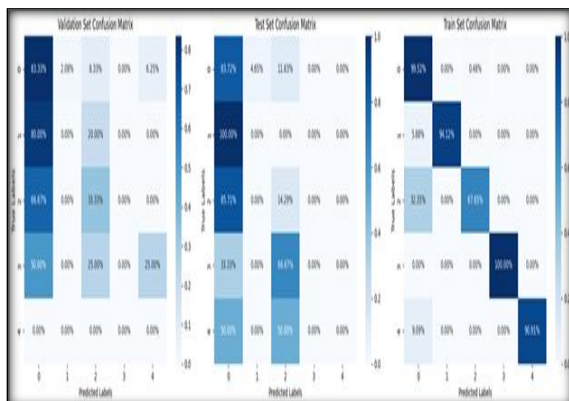


Figure 3 shows confusion matrices (of accuracies) of the validation set, test set, and train set – for the Multinomial Naïve Bayes Classifier. Confusion matrices show that Multinomial Naïve Bayes

Classifier is suffering from overfitting on the training data.

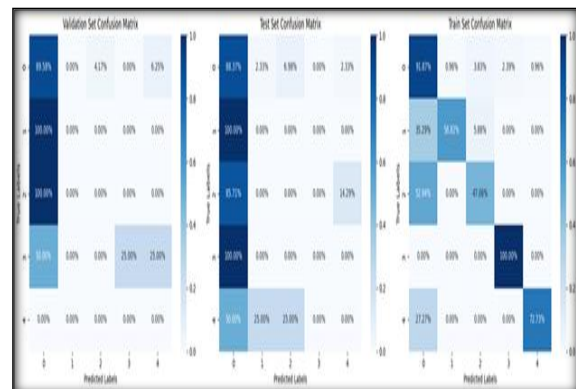
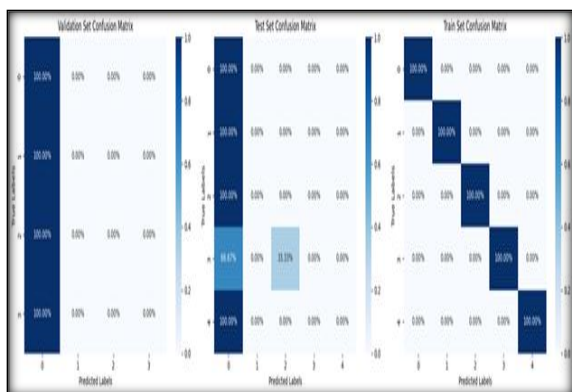


Figure 4 shows confusion matrices (of accuracies) of the validation set, test set, and train set – for the Random Forest Decision Tree Classifier with SoftMax. Confusion matrices show that Random Forest Decision Tree Classifier with SoftMax is suffering from overfitting on the training data.



Model Performance Comparison of the Shortlisted Models.

Table 2 describes overall comparison between different ML models which were shortlisted. Metrics like Accuracy and F1 Score are considered

**Table 2: Model Performance Comparison**

	<b>Accuracy</b>	<b>F1 Score</b>
<b>Multinomial/Multiclass logistic regression with Softmax activation function</b>	<b>Default config</b> Validation= 69% Test= 62% Train= 95%	<b>Default config</b> Validation= 0.68 Test= 0.58 Train= 0.95
	<b>With L2 regularization C=0.01</b> Validation= 80% Test= 71% Train= 74%	<b>With L2 regularization C=0.01</b> Validation= 0.71 Test= 0.60 Train= 0.64
	<b>With Early stopping</b> Validation= 68% Test= 61% Train= 95%	
	<b>With Grid Search</b>  <b>C=0.001, max_iter=100, multi_class=ovr, solver= "lbfgs"</b>  Validation= 71% Test= 80% Train= 95%	<b>With Grid Search</b> Validation= 0.59
<b>Multinomial Naive Bayes Classifier</b>	Validation= 65% Test= 73% Train= 83%	Validation= 0.58 Test= 0.68 Train= 0.83
<b>Random Forest Decision Tree (also with softmax AF)</b>	Validation= 71% Test= 78% Train= 100%	Validation= 0.60 Test= 0.70 Train= 1.0

The Train: Test: Validate ratio is defined as 70:15:15

Finally, gauging from the performances, we decided to go ahead with the Multiclass Logistic Regression Classifier:

The multiclass logistic regression classifier was used to classify children as having one or more specific learning disabilities based on their responses to the screening checklists. The algorithm used the SoftMax activation function to output the probability of each SLD for each child. The pros of using multiclass logistic regression include its simplicity, interpretability, and ability to handle multiple classes. The cons include its inability to

handle non-linear relationships between features and outcomes.

About the chosen Multiclass Logistic Regression Classifier with SoftMax:

- logistic classifier default config:penalty: 'l2', C=1.0, solver='lbfgs', max\_iter=100, multi\_class='autoaccuracy of the model:
- Validation = 69%
- Test = 62%
- Train = 95
- F1 Score of the model is
- Validation = 0.68
- Test = 0.58



- Train = 0.95

The ML algorithm involved initializing weights, applying SoftMax for predicted probabilities, and updating weights through gradient descent. [6] We developed algorithms for generating screening reports and recommending resources based on SLD probabilities. Data collection involved 50 real responses, augmented to 400 records. A preliminary study compared ML models, and the chosen multiclass logistic regression achieved an accuracy of 69% on validation and 62% on the test set.

Algorithms:

**The algorithm used are as followed**

**Inputs**

- X: Input features (screening checklist responses)
- y: Output labels (SLD categories)

**Outputs**

- Predicted probabilities of each SLD category for each input

Algorithm for the ML Classification Model

1. Initialize the weight matrix W and bias vector b to small random values.
2. Define the SoftMax function, which takes a vector of scores and returns a vector of probabilities that sum up to 1. The SoftMax function is given by.

$$SoftMax(z) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

where z is a vector of scores.

3. Compute the logits by multiplying the input features X with the weight matrix W and adding the bias vector b

$$z = X * W + b$$

4. Apply the SoftMax function to the logits to obtain the predicted probabilities of each SLD category

$$p = SoftMax(z)$$

5. Define the cross-entropy loss function, which measures the difference between the predicted probabilities and the actual labels

$$L = - \sum (y * \ln(p))$$

where y is a one-hot vector representing the true label of the input.

6. Update the weight matrix W and bias vector b using gradient descent to minimize the loss function

$$W = W - \eta * \frac{\partial L}{\partial W}$$

$$b = b - \eta * \frac{\partial L}{\partial b}$$

Where  $\eta$  is a hyperparameter that controls the step size of the update.

7. Repeat steps 3 to 6 for a fixed number of iterations or until the convergence criterion is met.
8. Output the predicted probabilities of each SLD category for each input as the result.

Algorithm for Data Augmentation

1. Collect the original 30 responses along with the target variable column
2. Drop the target column
3. Randomly select rows from existing rows
4. For each selected row, randomly flip '1' with '0' and '0' with '1'. This change would represent the noise in the data. Add this new row to the dataset
5. After satisfying the requirement of 400 rows, manually inspect each row.
6. If a row has a non-zero target value (representing the child having any SLD), identify the columns representing the questions that relate to that SLD
7. Modify the values in each such column to satisfy the 65% or greater threshold

Implementation of the App

The implementation phase concentrated on creating a mobile application with Flutter, a popular cross-platform framework. The goal was to develop an app that could effectively assess children aged 8 to 12 for specific learning disabilities (SLDs) such as dyslexia, dyscalculia, dysgraphia, and dyspraxia. To assist the collecting of responses from both parents and instructors across several categories connected with SLDs, a user-friendly interface was built.

During this study, a multidisciplinary team of educational psychologists, and SLD experts was established to assure a successful implementation of the idea. The app was developed to ensure that the app's design and functionality are in line with the study objectives.

Because of its ability to develop visually appealing and responsive user interfaces across multiple platforms, including iOS and Android, Flutter was chosen as the framework. An intuitive and engaging user experience by leveraging Flutter's wide array of pre-built UI components was created using flutter. Furthermore, the application included a machine learning (ML) model that analyzed parent and teacher replies.

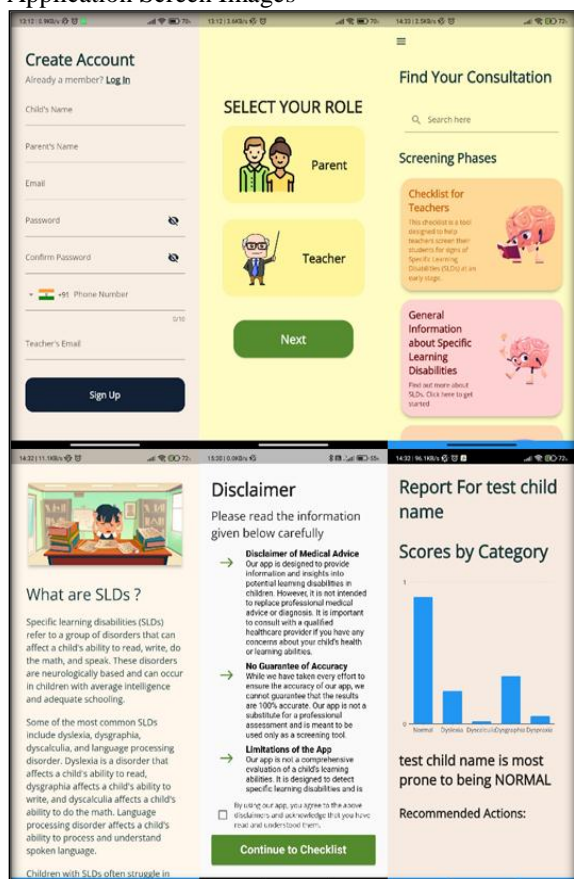
Multiclass Logistic Regression with a SoftMax activation function was the ML model used in the application. The following parameters were entered into the model: penalty='l2', c=1.0, solver='lbfgs', max\_iter=100, multi\_class='auto'. It analyzed the responses in order to discover probable SLD indicators. The goal was to use machine learning to give accurate and trustworthy screening results.

Various assessment measures were used to analyze the performance of the ML model. The model's accuracy was determined by comparing its predictions to known results. Validation accuracy

was found to be 69%, test accuracy to be 62%, and training accuracy to be 95%. The F1 score, a measure that balances precision and recall, was also computed. The F1 score for validation was 0.68, the F1 score for testing was 0.58, and the F1 score for training was 0.95.

The implementation step entailed creating a mobile app with the Flutter framework. A Multiclass Logistic Regression ML model with specified parameter settings was used in the application. The accuracy and F1 score findings showed that the model performed satisfactorily. These findings confirmed the created application's ability to deliver accurate and reliable screening results for SLDs in youngsters.

### Application Screen Images



### Testing and Verification

The testing and verification phase focused on evaluating the functionality, performance, and effectiveness of the developed mobile application. Rigorous testing was conducted to ensure that the application performed as intended and produced reliable results. The testing process comprised two main aspects: functional testing and validation testing.

Functional testing involved systematically examining each feature and functionality of the application to ensure proper operation. It encompassed tests to verify the user interface, questionnaire navigation, data collection, and result

generation. The app was checked for any errors, bugs, or inconsistencies throughout the application. Validation testing aimed to assess the accuracy and reliability of the screening results generated by the ML model. To establish the validity of the application's results, a benchmark dataset of children diagnosed with SLDs was utilized. The responses from both parents and teachers were collected for this dataset. The obtained data was compared with the known SLD diagnoses to measure the effectiveness of the application in correctly identifying SLD cases.

Furthermore, feedback from users, including parents and teachers, was collected through surveys and interviews to gauge their satisfaction and gather insights for further improvements. User feedback played a crucial role in validating the application's usability and identifying areas for enhancement.

The testing and verification phase provided valuable insights into the performance of the application, allowing for refinements and optimizations. By rigorously testing and validating the developed mobile application, we aimed to ensure its reliability and effectiveness in screening children for SLDs.

## CONCLUSION

A mobile app that enables parents and teachers to screen children for specific learning disabilities using a series of questionnaires was developed in this study. The app has been designed to be user-friendly and accessible, with a simple and intuitive interface. Our results show that the multiclass logistic regression model with the SoftMax activation function used in our app is effective in generating probabilities for each type of SLD.

Clinical psychologists and occupational therapists were consulted to develop the questionnaires used in our app, and the data collected has been used to train the model. The app also provides location-based recommendations for nearby clinical psychologists and occupational therapists for those with high probabilities of SLDs, ensuring that families can easily access the resources they need.

The ML Model was the key part in the App as it was responsible for the whole screening process. The training accuracy of 95 % and the validation accuracy of 69 % was obtained through the model.

The development of this app represents an important step towards improving the identification and intervention of SLDs in children. By providing a convenient and accessible way to screen for SLDs and connect families with the resources they need for professional guidance and official diagnoses, our app has the potential to make a real difference in the lives of children affected by SLDs.

We believe that this app has the potential to improve the early identification and intervention of SLDs, which can lead to better academic and social outcomes for children. We hope that this project will contribute to the growing body of research and

development in the field of digital health and that it will inspire further innovation in this area.

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