Machine Learning Based Developmental Capability Prediction: A Diagnosis to the Learning Capacity Disorder for Specially-Abled Children

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***Abstract*—Specially-abled people are recognized and acknowledged for their issues such as hyperactivity, learning disorder, proprioceptive sensory issues, problems in self-help skills and problems in various motor skills such as Gross Motor Skills (GMS), Fine Motor Skills (FMS) and Oral Motor Skills (OMS), This study sought to identify effective machine-learning-based classification models to predict developmental capability disorders and thereby addressing of the learning disorder issue at opportune time. We have used machine learning classification algorithms Decision Tree, Random Forest, K-nearest neighbors, and Logistic Regression for the developmental capability prediction of individuals. The generalized progress monitoring datasets were carried out by interpreting and visualizing gender, age and disability-specific developmental competence. We have collected dataset from an occupational therapist for the study. The results of the study show that the Random Forest algorithm has a high accuracy of 95% compared to other algorithms that we have implemented.**

***Keywords*—learning disorders, ASD, disability, occupational therapy, speech therapy, machine learning**

I. INTRODUCTION

Developmental capability refers to the ability of an individual to respond to the external environment and develop accordingly. Each individual has a different rate of development. The development process slows down due to various reasons like genetic disorders, environmental or social conditions, etc., but one of the important impetus is towards learning disorder, which will gradually retard the learning process of the individuals. This is a complex neurodevelopmental disorder that can have long-lasting impacts on individuals and their families. Delayed diagnosis and intervention can hinder the progress of children with this disability, leading to missed opportunities for early intervention and support. The motivation leading to this predictive model is to identify if the individual is carrying any traits, if not arrested, would ultimately lead to any type of disorder. In this study we have done an examination of cognitive abilities in children with disabilities associated with learning. Predicting developmental capability accurately and promptly is a significant challenge faced by healthcare professionals. Traditional methods often lack the efficiency and accuracy needed to identify this at an early stage. This research tries to relate the degree of disability and how it impacts the development process. The World Health Organization (WHO) framework [1] on the International Classification of Functioning, Disability and Health (ICF) computes the degree of disability at both individual and population levels. It defines three stages for human functioning: the first stage is at body level (considering body formation and functional domain), second is at activity level (considering all ADL that is activities of daily living) and third is at participation level (considering the socialization of person in varied surroundings), which is shown in Fig. 1. It also describes the reasons for disability: first the environmental factors (encompassing both physical and social surroundings) and second the personal factors (considering the health issues, age and family history). Types of disabilities are shown in Table 1. The extent of disability is estimated on the basis inability to perform at one or more of these stages [2].

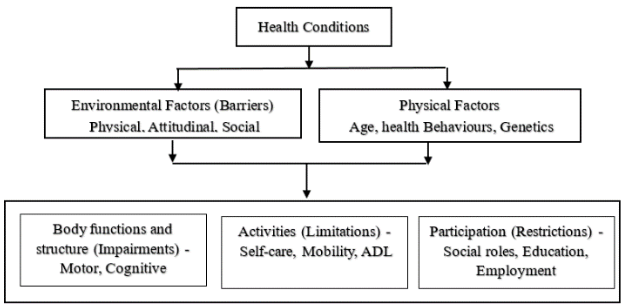

Fig. 1. ICF model.

Table 1. Types of disability

Disability	Description
Learning Disability (LD)	The ability to learn and apply the knowledge is delayed. The degree of impairment could vary. The learning process is slow. The prevalent problems are in reading and writing.
ADHD	The ability to pay attention is difficult due to hyperactivity. The sitting tolerance is also low. It is most prevalent in children. As a result, the learning process is also delayed. It is very important to utilize their excessive energy by indulging in physical activities.
Autism	Neuro-developmental disorder which affects the overall functioning and personality of an individual. Specialization of such individual is most effected. The self-time (time spent alone without interaction) is high.
Cerebral Palsy	The ability to maintain the balance and posture is delayed.

The developmental capability prediction model aims to achieve accurate predictions about whether an individual has a high developmental capability or not. The optimization of progress tracking and monitoring of individual is an essential

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aspect of this system. Most of the research focused on the application of technical advancements in implementing new learning methods that can be adapted for specially-abled children. Some of the state-of-the-art mechanisms used for assisting these children are based on machine learning and deep learning techniques.

Learning disorders, problems in various motor skills like gross motor skills, fine motor skills and oral motor skills, proprioceptive sensory issues, and problems in self-help skills issues are recognized as etiological factors for identifying specially-abled people and their learning disorder. The purpose of the study is to speed up the diagnosis process and construction of a learning disorder therapy plan by predicting the developmental capability of individuals in an early stage. The therapy plan is like a blueprint for the therapy process. It enlists all the activities to be carried out during the therapy sessions. The optimization of the progress tracking and monitoring is an essential aspect of this system.

The goal of this research work is to present a developmental capability prediction model using machine learning algorithms implemented in Python. By harnessing the power of advanced algorithms and data analysis techniques, machine learning offers a ground-breaking solution for predicting disability with the assistance of machine learning models, healthcare professionals can accurately identify autism-like genetic disorders at an early stage, allowing for timely intervention and tailored support. By leveraging machine learning in developmental capability prediction, we can revolutionize the way we approach this disorder, ensuring that individuals receive the care they need from an early age. Based on the prediction results, the practitioner can identify the areas where a child excels and where they may require additional assistance and can also provide tailored support, interventions, and resources that cater specifically to their strengths and challenges. By utilizing our state-of-the-art machine learning tools, we can make a significant impact on early intervention and treatment strategies for children with disabilities.

In our study, the functional level value is taken as the target variable, which is used for computing the output. The output has two possible values High and Low. This study mainly focuses on the prediction of three important parameters, namely, functional level, duration of therapy and the development area to be focused on.

II. Literature Review

Because of the worldwide increase in autism rates, research towards early identification of disability has accelerated. The absence of normal activities, rather than the presence of abnormal ones, is one of autism's most fundamental symptoms. Several researches have been carried out in this domain. Most of the research focused mainly on one disability that is ASD (Autism Spectrum Disorder. In this study, we concentrate on all forms of disability that have an impact on people's daily lives. The concept of eye-tracking for ASD prediction and quantitative analysis of the social response to ASD diagnosis were discussed in [3, 4]. The researchers have used feature transformation techniques like log and Z-score in their study [4]. They have used different machine learning algorithms for the study of different age groups.

Even though, certain advancements were made like highlighting the age for developing a mobile application for autism screening to predict ASD traits among people of varied age groups [5]. Numerous feature selection techniques were carried out to determine which machine learning classifier gave the best results in categorizing ASD risk factors in toddlers, children, adolescents and adults [6–9]. Linear discriminant analysis classifier and K-nearest neighbor techniques were used for ASD diagnosis.

The main objective was to find out whether children have ASD or not. Researchers also used a deep-learning model for ASD trait classification [10–12]. They used a 4-layer neural network to implement the deep-learning model. The activation functions applied are basic rectified linear unit (ReLU), Hyperbolic Tangent activation function (Tanh) and sigmoid activation function. The majority of the research used the pre-defined ASD dataset called the AQ-10 dataset is used for building the prediction model [13,14]. In this research, a web application is used for live data capturing and dataset creation. AI augment-based learning technique is used for behavior analysis and as an assistant for making decisions [15]. A machine learning framework with four feature scaling strategies like quantile, power, normalizer and MaxABS scaler [16].

In the study, the authors have proposed a phased methodology for early prediction of child disability [17]. The three-phase approach includes dataset identification and preprocessing techniques, data modeling using machine learning approaches like multilayer perceptron and evaluating the performance of the model. This study in [18, 19] focuses on creating significant feature signatures for the early detection of autism by applying automated machine learning along with feature ranking approaches on the Q-chat-based dataset.

The authors examined the use of technology in diagnosing and evaluating abilities in socialization, emotion management, communication and addressing behavioral issues [20]. The article also suggests standards for gaining knowledge of potential technologies with applications for the care and understanding of people with autism spectrum disorders. The Deep Convolution Neural Network (DCNN) ensemble-based classification framework was proposed in [21] to detect ASD disabilities.

Most of the current studies used the existing dataset like the AQ-10 dataset, which is mainly used for the detection of autism traits. In our study, we have collected a primary dataset from occupational therapist, based on disability traits in toddlers, kids, and teens.

III. Research Methodology

The proposed system is implemented in Python. The framework of the proposed study is depicted in Fig. 2. We have used Decision Tree (DT), Random Forest (RF), KNN classifier and Logistic Regression (LR) machine learning algorithms to study, predict and analyze developmental capability prediction of individuals. The collected dataset consists of the features of the age group between 3 and 17.

A. Individual Assessment

Each individual's performance was assessed in various development areas. The five areas of development that were taken into account in our study are Gross-Motor skills (GMS), Fie-Motor skills (FMS), Oral-motor skills (OMS), Cognitive Perceptual skills and Self-Help skills. These development areas help to understand and identify the co-occurrences of the disability conditions. For further examination, five different activities of each development area are taken into consideration. These areas and corresponding activities are shown in Table 2.

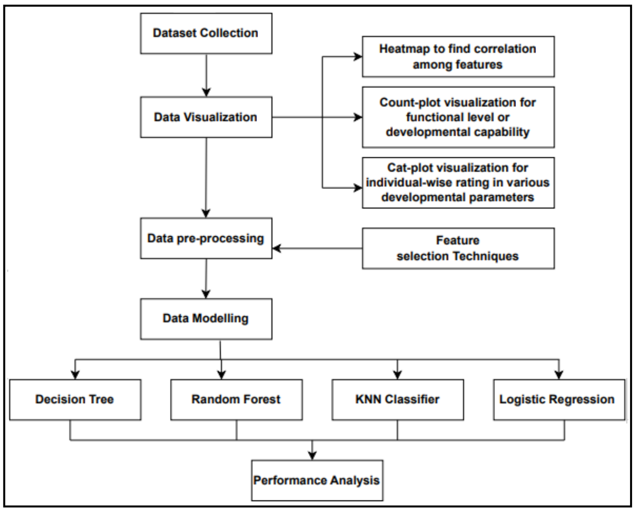


Fig. 2. Proposed study.

Table 2. Development areas

Area	Description	Activity
Gross-Motor skills (GMS)	Associated with mobility or body movements	Running, Bouncing, Ladder climbing, walking on balance beam, Going through Tunnel.
Fine-Motor skills (FMS)	Associated with more detailed or refined movements of wrists and hands.	String beads, Cloth Clip activity, Clay activity, building blocks, Scribbling with crayon
Oral-motor skills (OMS)	Associated with the oral cavity movements.	Sucking through straw, blowing (general), blowing candle, blowing whistle, protruding tongue
Cognitive Perceptual skills	Associated with overall thinking, understanding and applying of pre-learned knowledge	Matching objects, Putting shapes, Solving-puzzles, Identification of objects, identification of pictures
Self-Help Skills	Associated with the ability of the child to do self-care tasks and routine daily tasks.	Dressing, eating, bathing, tooth brushing, Hygiene maintenance

In this research we have done an examination of cognitive abilities in children with disabilities associated with learning. Cognitive perceptual skills associated with overall thinking, understanding and applying of pre-learned knowledge are the parameters for this examination. A rating scale approach was used where the lowest value being 1 and the highest being 4, which is shown in Table 3.

Table 3. Rating scale

Rating	Description
1	Does not Initiate
2	Partially Initiates
3	Initiates
4	Completes

B. Prediction

This research predicts three output values, functional level, duration and development areas to be focused on, which is shown in Table 4.

Table 4. Prediction parameters

Sr. No.	Value	Possible value
1	Functional level	High or Low
2	Duration	6 months, 1 to 2 years, 2 to 3 years, more than 3 years
3	Development Areas to be focused on	Gross-motor skills, Fine-motor skills, Oral-motor skills, Cognitive perceptual skills, Foundation development established in every area

1) Functional level

This output feature predicts the developmental capability of an individual. The functional level helps to identify the degree of disability of a child. For example, if there is an autistic child then with the help of the functional level we can identify at which level of disability spectrum the child is. The value of functional level high means that all the motor skills like GMS, FMS, etc. are properly developed. The child with proper therapy can carry out a normal life. A functional level value low means that all the motor skills of the child are not properly developed. Extensive therapy and care are necessary. With the help of this analysis, the therapist can plan the therapy process and decide to make modifications to the ongoing therapy process.

There are five development areas. Each area comprises five activities. For each activity, the highest rating possible is 4 and the lowest rating is 1. The therapy process takes into account the total of all the ratings. Then, the maximum possible total rating of an individual is computed as in Eq. (1):

$$M = n \times p \times h \tag{1}$$

where n is the total number of development areas, p is the total number of activities of each development area and h is the highest possible rating given to the individuals. In our study, h is equal to 4. Since each of the five development areas in our study has five distinct activities, the value of n and p is 5. M is calculated as follows:

$$M = 5 \times 5 \times 4 = 100$$

The disability spectrum can be classified as high-functional and low-functional. High functional individuals' brain growth will be taken into account as being greater than 50% [22, 23]. The threshold value, number and type of developmental areas and corresponding functional activities were identified with the help of an occupational therapist. Based on the value computed for M, the threshold value, T, is computed for identifying the functional level value using Eq. (2).

$$T = M/2 = 100/2 = 50 \tag{2}$$

This threshold value decides whether an individual has high developmental capability or low developmental capability.

The equation for computing an individual's total rating, TR, is given in Eq. (3).

$$TR = \sum_{i,j=1}^{5} R_{i,j} \tag{3}$$

where $R_{i,j}$ is the rating of j^{th} activity of i^{th} development area.

Then the average value of TR is calculated to identify the diagnostic evaluation by the occupational Therapist. This developmental capability prediction process is shown in Fig. 3.

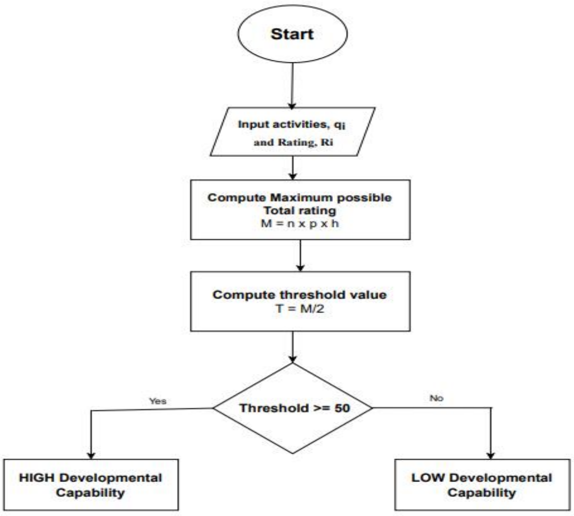


Fig. 3. Developmental capability prediction process.

2) *Duration*

Duration is a prediction parameter which predicts the time required to complete the basic foundation therapy of the individual. It is an estimated value based on the average rating computed. Since therapy is an ongoing process, the duration can be increased or decreased as per user's requirement. Therapy is a support given to an individual to normalize the learning and behavioural disorder. It can reduce the impact of the disability and help in the normal functioning of an individual. The total rating computed is used for calculating the average rating. Average rating= TR / p, where TR is the total rating and p is the number of activities of each development area. Based on this average the duration value estimate is computed as shown in Fig. 4. The occupational therapist begins diagnostic evaluation and decides the therapeutic strategies based on the duration identified.

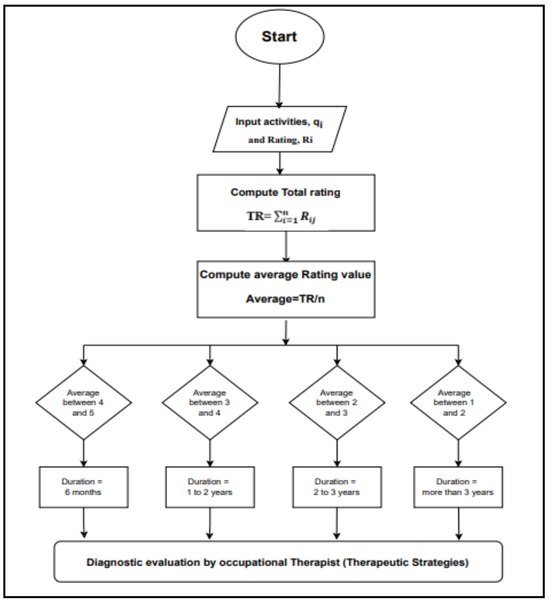


Fig. 4. Foundation therapy duration identification of the individual.

3) *Development area*

This predicts the development area that requires most attention. This will help in designing a better therapy plan for the individual. This takes into account the rating of each activity in that area. There are four areas. Each area has five activities respectively. The rating in each activity is considered for the prediction. The rating scale varies from 1 to 4. If the rating is less than or equal to two in any activity, then that area needs to be focussed on. Otherwise, the foundation development is established in every area.

IV. Implementation of Machine Learning Approaches

We have used primary data for the analysis and prediction of developmental capability. The dataset collected from the occupational therapist is used in the prediction model. In this research, we have taken 80% of the dataset as a training dataset and 20% as a testing dataset. This research used machine learning algorithms Decision Tree, Random Forest, KNN classifier and Logistic Regression for developmental capability prediction. The algorithms used multiple visualization technique heatmap for finding out the correlation among different features. The decision tree is further visualized using text representations and tree-like representations. The therapist assesses an individual on various development parameters like Gross-Motor Skills (GMS), Fine-Motor Skills (FMS), Oral-Motor Skills (OMS), and cognitive-perceptual skills with the help of a rating- scale. The main objective of the prediction system is to get a probabilistic value for the high developmental capability of an individual. This machine learning prediction model helps to identify whether there is improvement or there is a need to change the strategy of development.

A. *Feature Description*

We have collected data from an occupational therapist. The dataset collected consists of 28 features and 1 target value. These 28 features are defined by the therapist. From the dataset used to train our algorithm, only the name attribute, which has no bearing on prediction, has been eliminated. The functional level is the target value which has two possible values High and Low. This value is a probabilistic estimation of the developmental capability of an individual. If the calculated functional level value is greater than or equal to 0.5, then the developmental capability is considered as high and low otherwise. The feature description is depicted in Table 5.

Table 5. Feature description

Feature	Description
Name	Name of an individual
Jumping	Rating given in jumping activity under GMS
Bouncing	Rating given in bouncing activity under GMS
Ladder climbing	Rating given in ladder climbing activity under GMS
Walking on balance beam	Rating given in walking on balance beam activity under GMS
Going through tunnel	Rating given in going through tunnel activity under GMS
Stringing beads	Rating given in stringing beads activity under FMS
Cloth clip activity	Rating given in cloth clip activity under FMS
Clay activity	Rating given in clay activity under FMS

Building blocks	Rating given in building blocks activity under FMS
Scribbling through crayon	Rating given in scribbling through crayon activity under FMS
Sucking through straw	Rating given in sucking through straw activity under OMS
Blowing	Rating given in blowing activity under OMS
Blowing candle	Rating given in blowing candle activity
Blowing whistle	Rating given in blowing whistle activity
Protruding tongue	Rating given in protruding tongue activity
Matching objects	Rating given in matching objects activity
Putting shapes	Rating given in putting shapes activity
Solving puzzles	Rating given in solving puzzles activity
Identification of objects	Rating given in identification of objects
Identification of pictures	Rating given in identification of pictures
Total	Sum of all the ratings
Avg	Average of all the ratings given in each area
gender	Gender of Individual
duration	Estimated time for therapy
category	The specific age category
type	Type of disability
Functional level	The developmental capability prediction

B. *Correlation among Features*

Correlation between different features is visualized with the help of a heatmap, which is shown in Fig. 5. The darker shade represents a higher value and the lighter shade represents a lower value.

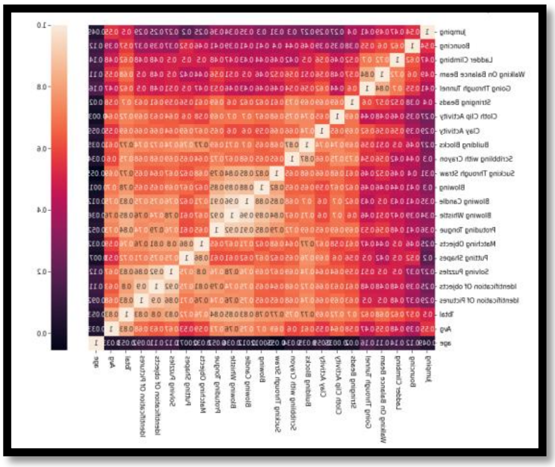


Fig. 5. Correlation among different features.

C. *Feature Selection*

Feature selection methods have a major role in maintaining system performance. The data is processed for missing values. We use the correlation heatmap to identify feature correlation. If the feature is highly correlated, then handle the missing value otherwise drop the unwanted feature. The dataset contains both numerical and categorical data. It is very important to convert categorical data into numerical form before data modelling. The conversion of all the object type features into numerical values is done using label encoding.

D. *Machine Learning Models*

1) *Decision tree*

A decision tree is a classification prediction algorithm. The Gini index is used to select the splitting attribute and based on this splitting attribute the decision tree is divided into two parts. The Gini index value is computed as follows:

Gini (D) =1−∑Pi, where Pi is the probability that a record D belongs to class C.

In this research, the target value, functional level, is used to compute the output. Output prediction depends on the functional level value. The condition is functional level ≧ 0.5 goes for class:0 (yes: functional level is high) and functional level <0.5 goes for class:1(no: functional level is not high).

2) *Random forest*

Random Forest algorithm builds decision trees on different samples and voting is carried out, as shown in Fig. 6. The majority vote is considered for classification. The RF approach uses numerous decision tree classifiers to improve the performance of the model DT are generated at random from the instances of the training set. As a result, each decision tree makes predictions. By majority vote, the model's final prediction is chosen.

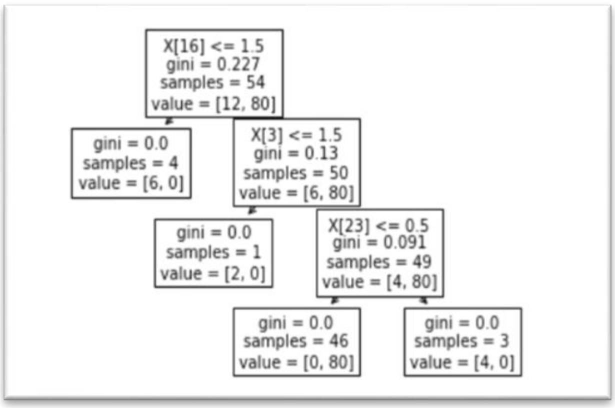


Fig. 6. Tree-like representation for Random Forest.

3) *KNN classifier*

K-Nearest Neighbor is used for classifying data based on the threshold value specified. The number of k-nearest values is computed using the Euclidean distance. Euclidean distance value is computed as follows:

$$\text{Euclidean Distance} = \sqrt{\sum(x_i - y_i)^2}$$

where x_i and y_i are the Euclidian vectors

4) *Logistic regression*

Logistic regression uses probabilistic estimation for classification. The logistic regression function $p(x)$ is the sigmoid function of

$$f(x): p(x) = 1 / (1 + \exp(-f(x))$$

This function p(x) is used to predict the probability that a given x is either closer to 0 or 1.

V. Results and Discussion

A. *Dataset Analysis*

The main objective is to track and monitor monthly data for the behavioural analysis of individuals. So, for the performance evaluation and model prediction, we have carried out a study using machine learning algorithms, on the dataset collected.

B. Machine Learning Algorithm Analysis

A confusion matrix was built to visualize how well this strategy performed. Confusion matrix of Decision Tree, Random Forest, KNN classifier and Logistic Regression on test data is shown in Fig. 7.

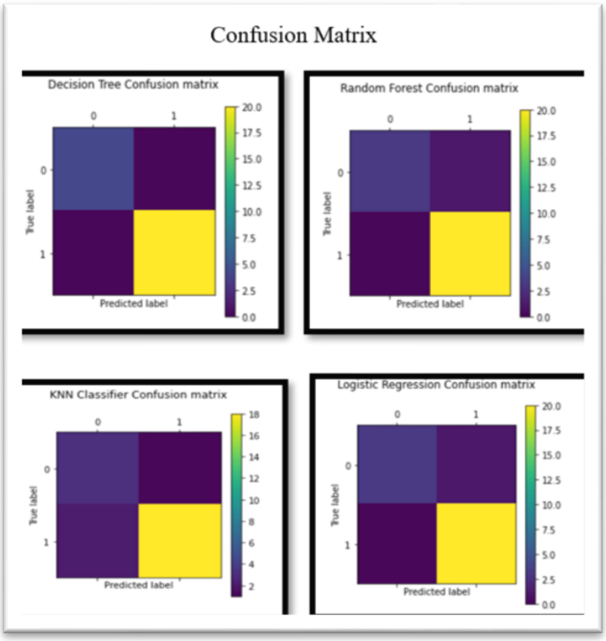


Fig. 7. Confusion matrix.

1) Text representation analysis

In this research, the functional level value is used to compute the output. The output can be visualized using text representation and tree-like structure, which is shown in Fig. 8.

```
|--- feature_23 <  0.50
|   |--- class: 1
|--- feature_23 >= 0.50
|   |--- class: 0
```

Fig. 8. Text-representation for decision tree.

The feature taken as a splitting attribute is "functional level". The values less than or equal to 0.5 are classified into class 1(no: functional level is not high) and the values greater than 0.5 are classified into class 0 (functional level is high).

2) Decision tree analysis

From the text representation analysis, it is observed that the splitting attribute is "functional level". In the decision tree shown in Fig. 9, 76 samples are classified into class 0 (developmental capability is high) and 16 samples are classified into class 1 (developmental capability is not high).

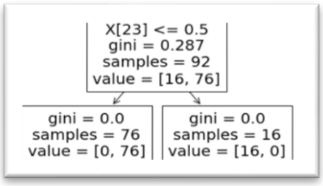


Fig. 9. Decision tree analysis.

3) Random forest analysis

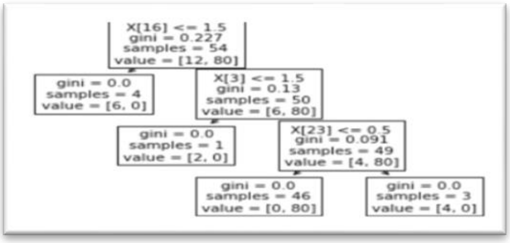


Fig. 10. Random forest analysis.

As shown in Fig. 10, the main splitting attribute is "Putting Shapes". Out of which 4 samples are classified (developmental capability is not high). These 4 samples have a rating less than or equal to 1.5. 50 samples are remaining. For this 50 sample, the splitting attribute is "Walking on Balance Beam". One sample has to have a rating of less than or equal to 1.5 and is classified into class 0. Class 0 indicates that the developmental capability is not high. For the rest of the 49 samples the splitting attribute is "functional level_high".46 samples having a value greater than 0.5 are classified into class:0 (developmental capability is high) and the 3 remaining samples are classified into class:1 (developmental capability is not high).

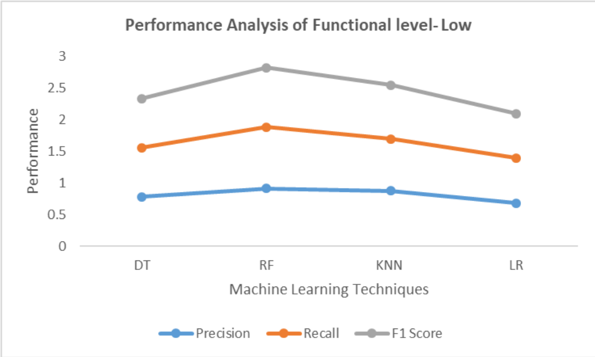
4) Performance analysis

The performance of the machine learning algorithms is evaluated using various parameters. These parameters are the accuracy of each algorithm, precision, recall and F1 score. The result of the evaluation parameters for each algorithm is tabulated in Table 6. The accuracy of DT, RF, KNN and LR is 78.15%, 95.38%, 84.54% and 72.63% respectively. The RF algorithm produces the most reliable prediction whereas the LR algorithm produces the least reliable prediction. The functional level performance analysis of different models is depicted in Fig. 11.

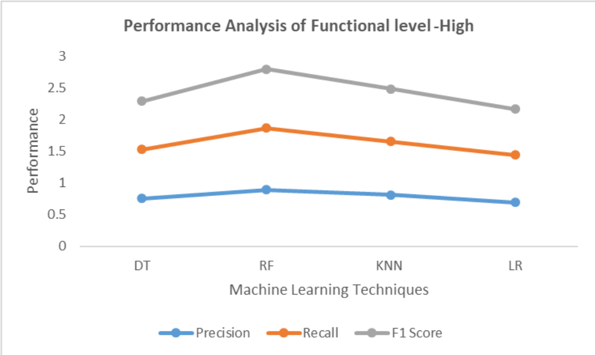
This model acts as a litmus test to further aid the initial investigation process towards the formulation of strategic plan for impactful occupational therapy. The findings highlight the strong relation between comorbidities of learning disorder and developmental capability. Our experimental study will give a rudimentary approach to carry forward their behavioural analysis and learning disorder without any further delay.

Table 6. Evaluation parameter result

Algorithm	Functional Level	Precision	Recall	F1 Score	Accuracy
DT	low	0.7831	0.7712	0.7771	0.7815
	high	0.7543	0.7747	0.7644	
RF	low	0.9151	0.9645	0.9392	0.9538
	high	0.8918	0.9731	0.9307	
KNN	low	0.8733	0.8233	0.8476	0.8454
	high	0.8144	0.8415	0.8277	
LR	low	0.6828	0.7117	0.6970	0.7263
	high	0.6947	0.7505	0.7215	



(a)



(b)

Fig. 11. Functional level performance analysis of different models: (a) Functional level value- Low; (b) Functional level value- High.

VI. Conclusion

The developmental capability prediction model aims to achieve accurate predictions about whether an individual has a high developmental capability or not. In this research, we have used and explored DT, RF, KNN, and LR classification algorithms for the developmental capability prediction of individuals. In our study, we have collected a primary dataset from occupational therapist, based on disability traits in toddlers, kids, and teens. To identify the disability traits, five developmental areas were identified and for each developmental area, five activities were recognized. The results of our research show that the RF algorithm produces the most reliable prediction, which is 95.38% whereas the DT algorithm produces the least reliable prediction, which is 72.63%. The main goal of this research was to advance the existing research by creating the model in a novel and creative method and to make the approach practical and simple to apply to real-world scenarios. This prediction is the precursor for the identification of the individual's disability and timely addressing of their learning disorder. We would like to extend our study using deep learning algorithms with more datasets for improving the performance of machine learning algorithm and further pursue the research on the learning disorders like dyslexia, dyscalculia and dysgraphia.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

GB and VA conceptualized and conducted the research, NP and MD analyzed the data, PC conducted the experiments and wrote the manuscript, SV revised the discussion section and SP proofread the paper. All authors had approved the final version.

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