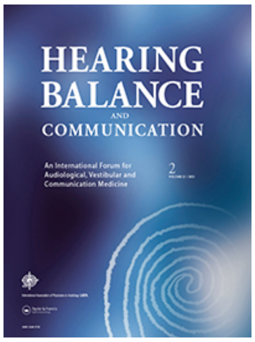

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ORIGINAL ARTICLE

A scoring system for cochlear implant candidate selection using artificial intelligence

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ABSTRACT

Objective: Cochlear implant (CI) candidate selection is a lengthy, complicated process that entails subjective judgment on the interaction of multiple pre-operative variables. It is assumed that setting a scoring system for the process of CI candidate selection would help in precise and reliable decision making. This would also provide a tool that would help in providing a better quality of life for CI patients.
Methods: Retrospective cohort study was held out in three post-CI rehabilitation centers. A total of 100 children records were analyzed with two statistical methods; conventional and Artificial Intelligence (AI) using Machine Learning. Language age deficit, phonological deficit, and social deficit were invented as new measures of CI performance; used to represent the developmental delay of those children in a single numeric value (in months).
Results: Artificial Intelligence analysis surpassed conventional statistical methods for the prediction of the outcome measures of post-CI performance. This was clearly expressed using linear regression models. The AI classification model validation for predictive accuracy of language age deficit, phonological deficit, and social deficit were 56.66%, 88.11%, and 40.46% respectively.
Conclusion: The production of a preliminary CI scoring model used for prediction of performance of patients was achieved. More data should be collected and fed to the software in order to improve its performance.

KEYWORDS
Cochlear Implant; artificial intelligence; machine learning; scoring; candidate selection

1. Introduction

Cochlear implant (CI) is a widely accepted rehabilitation choice for children who receive little or no benefit through amplification and have unfavourable outcomes in listening, spoken language, literacy, and social/emotional well-being [1,2]. Yet, there is a common clinical inquiry in paediatric cochlear implantation about 'Who will achieve success?' as each patient's outcome changes and varies depending on his/her baseline pre-operative assessment. Moreover, success of CI depends on many factors including careful candidate selection, skilful surgeon, comprehensive post-operative rehabilitation and realistic expectations [3].

Each single pre-operative variable may have been addressed in previous work, alone [4,5], or in combination with some other variables [6,7] as contributing factors affecting the outcome, but none addressed the combination of multiple variables found in each child in real life. In most instances, the prediction of success is made based on subjective judgement of the CI team for each patient with no objective tool (score) controlling this process.

The absence of such a scoring system prohibits us from measuring the added value for each patient, and, accordingly, we cannot objectively improve the outcome. '*If we can't measure it, we can't improve it*' as said by Peter Drucker [8]. The term of added value is originally used in economics to describe the extra value created above the original value of something, or the enhancement made by the company to its product or service [9].

Due to the heterogeneity of data and the large number of the variables affecting the CI outcome, setting a scoring system with the ordinary statistical methods was difficult. So the authors planned to use Artificial Intelligence (AI) and Machine Learning (ML) instead. Machine learning (ML) is a type of AI

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that uses algorithmic methods that help machines to solve problems without pre-set computer bases algorithms. One of the main differences between ML and traditional statistics is that traditional statistics try to detect correlations between variables, while ML focuses on making predictions as accurate as possible. ML methods capture the nonlinearities between variables, and visualise them in order to improve interpretability [10].

2. Methods

This retrospective cohort was a multi-center study which included 100 records for children who attended three oro-aural rehabilitation centres and were implanted in the period from 2012 to 2020. Inclusion criteria were children with pre-lingual hearing loss, currently using unilateral CI and whom received rehabilitation equal to/or more than 1 year. Incomplete records and those who had re-implantation, intra- or post-operative complications, and those diagnosed with ANSD were excluded. In the current study, 45 pre-operative variables were studied (Table 1).

Operative and early post-operative history was obtained to exclude cases with complications, and to identify the exact time of initial stimulation of the device. Detailed post-operative history was taken as regards device type, audiological data, speech and language assessment, rehabilitation type and frequency, and latest calculated language, phonological, and social ages.

Calculations for the post-operative outcomes were done as follows: Average duration of CI use was calculated as the time elapsed since the initial stimulation of CI to the time of the latest assessment of the language, phonological, and social ages. Satisfactory aided response was defined as aided warble tone threshold ≤39 dB HL. Language age was measured using the modified Arabic PLS4 [12] considering 8 years as the ceiling [13]. Phonological age was calculated as the sum of language age and the duration of amplification with CI divided by 2 [14]. Social age was measured using Vineland Social Maturity Scale (VSMS) (1965).

There was high variability in the differences between the chronological ages of the children and their current corresponding language, phonological, and social ages. In order to overcome this problem; the authors agreed to use deficit outcomes to represent the developmental delay of those children in a single numeric value (in months).

- Language age deficit: the difference between the chronological age at time of evaluation and the corresponding language age at that same time.
- Phonological deficit: the difference between the expected phonological age and the current phonological age at time of assessment.
- Social deficit: the difference between the chronological age and the current social age of the child.

Data collected were analysed through two methods to construct the prediction models (Figure 1).

2.1. Conventional statistical method

Data were analysed using IBM Statistical Package for Social Sciences (SPSS) software, 21st edition, IBM, United States. Linear regression models for the prediction of outcome were used.

Table 1. Variables included in the current study.

Studied variables			
• Sex.	• Prematurity.	• EEG.	• Socioeconomic status.
• Average duration of AD[a].	• Post-febrile HL.	• Middle ear condition prior surgery.	• Pre-implantation rehab. Services.
• Average duration of hearing.	• Syndromic HL.	• Psychological status of child.	• Binaural aided threshold.
Cause of hearing loss:	• Cochlear anomalies.	• Parental consanguinity.	• Binaural aided SRT.
• Prenatal/perinatal/postnatal.	• Post-head trauma.	• Family history of HL.	• Binaural aided discrimination.
• Familial HL.	• Idiopathic HL.	• Siblings with HA/CI.	• Listening skills score.
• Progressive HL.	• Multiple disabilities.	• Hearing impaired parents.	• Auditory skills score.
• Maternal infections.	• Residual hearing[b].	• Mother education.	• Receptive language.
• Jaundice.	• Fair response of HA at some point of time[c].	• Father education.	• Expressive language.
• Hypoxia.	• Age at CI.	• Family support.	• Gesture.
• Low birth weight.	• Side of implantation.		• Imitation.
• Ototoxicity.	• Device type.		
	• Intelligent Quotient[d].		

[a]Average duration of (AD) Auditory Deprivation (in months); was considered the duration since the onset of hearing loss till the 1st hook-up.
[b]Children considered having residual hearing if they had hearing threshold of ≤70 dB HL up to 1 kHz preoperatively [11].
[c]Fair response of hearing aid at some point of time was considered present if children had average aided PTA thresholds of ≤60 dB HL (at some point of time) before they get their implants.
[d]Intelligent Quotient test results were obtained using Stanford-Binet test Ver.4.

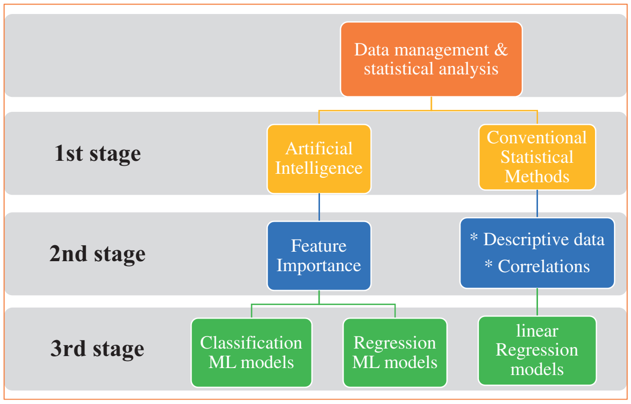


Figure 1. Methods of statistical analysis.

Table 2. Classes of language age deficit.

Slight delay: (1–12 m[a])	Moderate delay: (>36–48 m)
Mild delay: (>12–24 m)	Moderate to severe delay: (>48–60 m)
Mild to moderate delay: (>24–36 m)	Severe delay: (>60 m)

[a]m: Month.

Table 3. Classes of both phonological and social deficits.

Slight delay: (1–6 m[a])	Moderate delay: (>18–24 m)
Mild delay: (>6–12 m)	Moderate to severe delay: (>24–30 m)
Mild to moderate delay: (>12–18 m)	Severe delay: (>30 m)

[a]m: Month.

2.2. Artificial intelligence ML models

While using AI to create the predictive models, the authors agreed to consider the following classes for categorisation of the degree of delay of language, phonology, and social development, Tables 2 and 3.

The following steps were done to create the final Regression, and Classification Prediction Models; using Python (in 1st step), and WEKA 3.9.5 with console data mining tool software (in 2nd–4th steps):

1. Feature Importance: techniques that assign scores to the input features (variables) based on how useful they are in predicting the outcome, using Catboost ML model.
2. Class balancer filter: applied to phonological, and social classes to allow for better predictive performance in classification prediction models.
3. Model training: algorithms applied to a training set (group of study cases where input variables and output deficits are known) to uncover patterns between its features (variables) and the target outcomes. Five different ML algorithms were used for prediction of the classes of language age, phonological, and social deficits. Five ML algorithms (Regression models) were used for prediction of language age, phonological, and social deficits (to predict the exact deficit in months). All algorithms used belong to four broad categories; Probabilistic classification, K-Nearest Neighbour (KNN), Support Vector Machines (SVM), and Tree-based classification [15].
4. Predictive scores construction: the trained model was applied to a new dataset (test cases). Then, the models returned outcomes in the form of probability scores for classification deficits and estimated averages for regression deficits. This step was considered a sort of internal validation of the current predictive models.

Four main evaluation metrics were calculated to evaluate the classification models and calculate the error. *Accuracy* is used as a single measure to summarise model performance. *Precision or Positive Predictive Value (PPV)* is a metric that quantifies the number of correct positive predictions made. *Recall (sensitivity)* is a metric that quantifies the number of correct positive predictions made out of all positive predictions that could have been made. *F-measure* is a way that combines both precision and recall into a single measure. (Equations 1-4).

$$Accuracy = (TruePositives + TrueNegatives)/\ \mathrm{n} \times 100 \tag{1}$$

$$Precision = TruePositives/(TruePositives + FalsePositives) \tag{2}$$

$$Recall = (True\ Positives)/(True\ Positives + False\ Negatives) \tag{3}$$

$$F - Measure = (2 \times Precision \times Recall)/(Precision + Recall) \tag{4}$$

where, n is the number of observations.

To evaluate the predictions made by the regression models, we calculated the Mean Absolute Error (MAE) which represents the mean value of the absolute differences between the actual values and the predicted model values (Equation 5).

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\ y_i - \bar{y_i}\ | \tag{5}$$

where, $\bar{y_i}$ *and* y_i denote the true and predicted model values of the i^{th} observation, respectively.

Coefficient of determination (R^2) for regression tasks was used to measure the relative closeness of the predicted values to the actual values. R^2 has a

Table 4. Language age deficit classification ML models.

Classifier	Accuracy %	Precision	Recall	F-measure
AdaBoost SMO	**56.66**	0.699	0.567	0.566
SMO	53.33	0.638	0.533	0.533
Random Forest	50.00	0.571	0.500	0.494
Naïve Bayes Multinomial	43.33	0.357	0.433	0.386
Naïve Bayes	40.00	0.483	0.400	0.396

Bold value refers to highest classification accuracy.

Table 5. Phonological deficit classification ML models with Class Balancer Filter.

Classifier	Accuracy %	Precision	Recall	F-measure
IBK	**88.12**	0.916	0.881	0.885
Random Forest	86.00	0.909	0.860	0.868
AdaBoost Naïve Bayes	85.87	0.907	0.859	0.857
Naïve Bayes	82.71	0.873	0.827	0.828
Naïve Bayes Multinomial	74.26	0.797	0.743	0.735

Bold value refers to highest classification accuracy.

Table 6. Social deficit classification ML models with Class Balancer Filter.

Classifier	Accuracy %	Precision	Recall	F-measure
Simple Logistic	**40.46**	0.351	0.405	0.370
Bagging Hoeffding Tree	33.65	0.304	0.337	0.295
AdaBoost SMO	31.81	0.321	0.318	0.302
Naïve Bayes Multinomial	30.28	0.394	0.303	0.279
Naïve Bayes	29.36	0.237	0.294	0.244

Bold value refers to highest classification accuracy.

value between 0 and 1. A higher R^2 value represents a higher accuracy of the predictive model (Equation 6).

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \bar{y_i})^2}{\sum_{i=1}^{N}(y_i - \hat{y})^2} \tag{6}$$

where $\hat{y}$ denotes the mean true values of the observations.

3. Results

3.1. Conventional statistical method

In the current study, 60% male, and 40% female children whose ages ranged from (36-168) months, with Mean ± SD of 78.28 ± 31.63 respectively were included.

Figure 2 shows the distribution of deficit classes among study group;

Figure 3 shows the imbalanced distribution of study cases among deficit groups, specially phonological and social deficit classes.

Linear regression analysis (using ANOVA) revealed that the coefficient of determination (R^2) calculated for language age deficit, phonological deficit, and social deficit was 0.41, 0.32, and 0.26 respectively which denoted low predictive values.

3.2. Artificial intelligence ML models

3.2.1. Feature (variable) importance

This Bar chart showed that the most important variables affecting language age, phonological, and social deficits where; average duration of Auditory Deprivation (AD), and family support. Each accounted for more than (17%) of the deferential weight of variables, while others contributed to a lesser extent as explained in the chart.

3.2.2. Class balancer filter results

1) Phonological deficit classes:

Figures 4 and 5 showed the changes applied to the distribution of phonological deficit classes, to overcome the imbalanced classes and for better classification results.

2) Social deficit classes:

Figures 6 and 7 showed the changes applied to the distribution of social deficit classes, to overcome the imbalanced classes and for better classification results.

In Language age deficit; classes were somehow normally distributed, so there was no need for the Class balancer Filter.

3.3. Classification predictive models

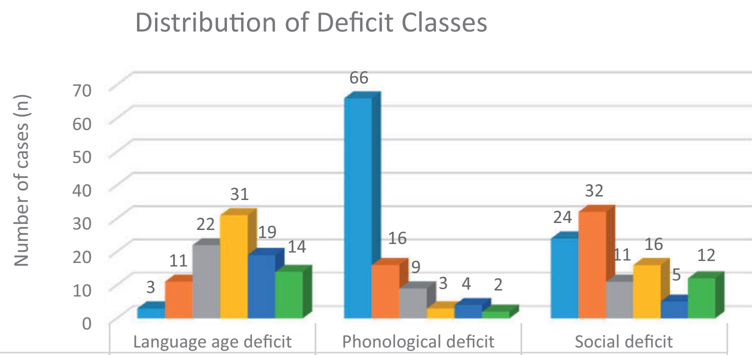
Tables 4–6 showed the different statistical measures calculated from the confusion matrix obtained after applying different ML classification models for language age deficit, phonological deficit, and social deficit respectively.

3.3.1. Regression models

Table 7 showed the regression models results in predicting language age, phonological, and social deficits (in months). Random Forest model outperformed other models in the prediction of language age, and phonological deficits with mean absolute error (MAE) of 8.95, and 5.51 months respectively. While Simple Linear Regression model showed the best prediction results for the social deficit with (MAE) of 8.29 months.

4. Discussion

The present study was done to construct a predictive scoring model for Cochlear Implant candidate selection for pre-lingually deafened children (HL ≥70 dB hearing loss prior to the age of 3 years) by utilising



	Language age deficit	Phonological deficit	Social deficit
Slight delay	3	66	24
Mild delay	11	16	32
Mild to moderate delay	22	9	11
Moderate delay	31	3	16
Moderate to severe delay	19	4	5
Severe delay	14	2	12

Outcome Measures

Figure 2. Distribution of deficit classes among study group.

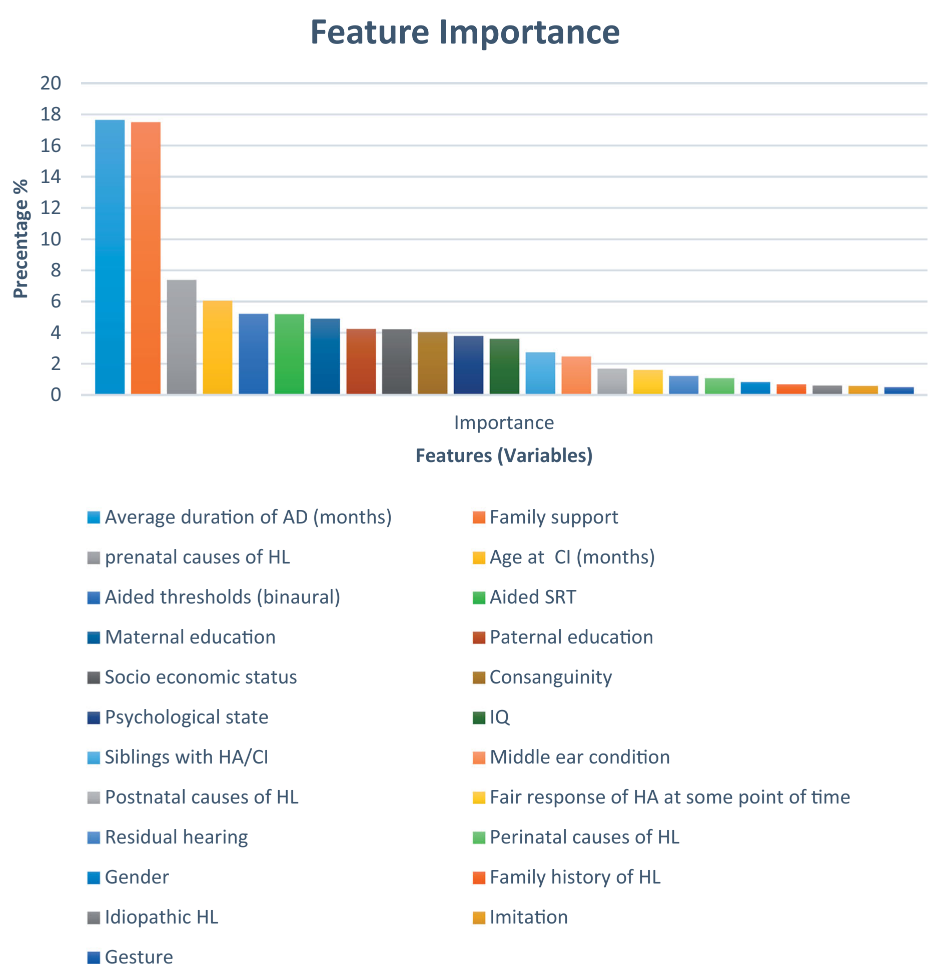


Figure 3. Deferential weight of important variables (according to study sample).

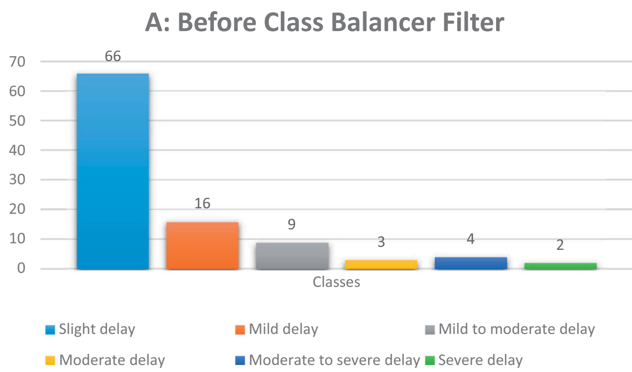


Figure 4. Phonological deficit classes before application of Class balancer filter.

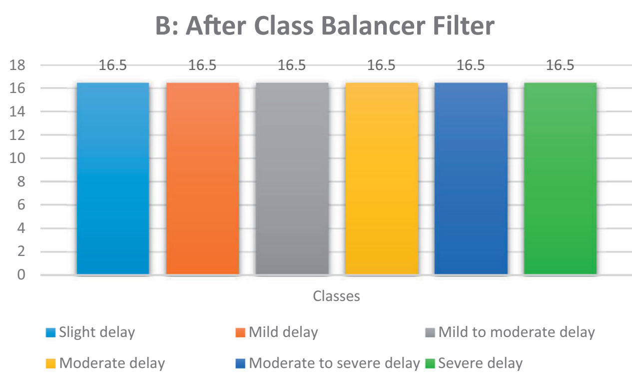


Figure 5. Phonological deficit classes after application of Class balancer filter.

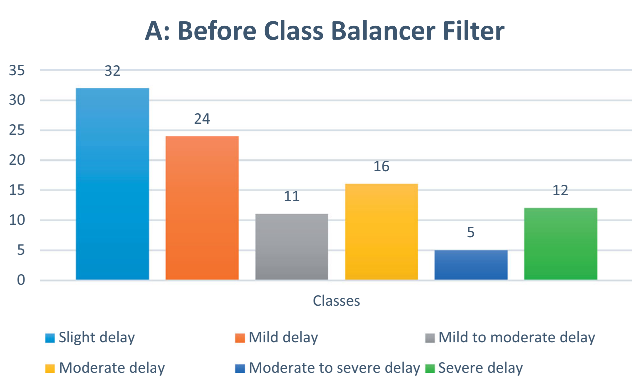


Figure 6. Social deficit classes before application of Class balancer filter.

Artificial Intelligence algorithms that adopts supervised machine learning prediction models.

Not only the associations of speech-language deficit outcomes with demographic and hearing history characteristics were examined in the current study, but also creating predictive scores for the outcome measures.

4.1. Conventional statistics

In the current study, we used deficit scores to measure the outcome performance of CI after one year or

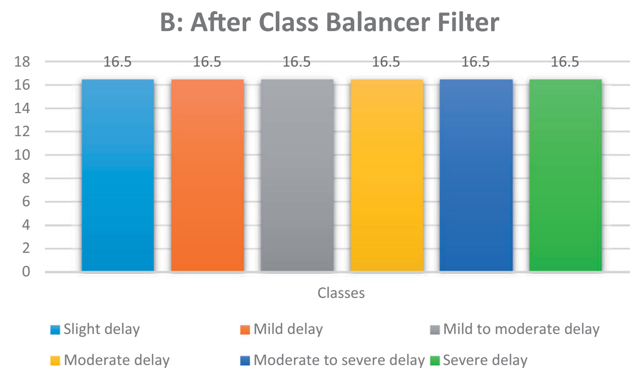


Figure 7. Social deficit classes after application of Class balancer filter.

more of rehabilitation, unlike other studies [16–18] which utilised Category of Auditory Performance (CAP) scores, Speech Intelligibility Rating (SIR) scores, and also Meaningful Auditory-Integration Scale (MAIS).

As well as considering a number of important factors examined in other studies [19–21] such as; age at implantation, IQ, presence of comorbidities; the present study included a number of independent variables that were not commonly included in regression analyses in paediatric CI studies, such as parental education, degree of family support, and presence of siblings using H.A/CI.

The low predictive behaviour of the linear regression models, for example, R^2 of the best fit models for language age, phonological, social deficits were 0.41, 0.32, and 0.26, respectively could be explained by the fact that their ability to explain variance of hearing outcome is limited, as linear models are capable of capturing only linear relationship between variables, which is not the case here. Heterogeneity and large number of data variables, complex features of each individual case, and the hidden interaction between the independent variables with each other made the relation between dependent and independent variables more complex than can be treated by simple linear regression models.

Also, metrics such as the proportion of variance explained do not give any indication of the model's ability to make predictions on unseen new patients, where predictions are usually less accurate [22].

Consequently, other (sophisticated) methods had to be introduced to study nonlinear relationships, and emphasise that hidden interaction between variables. Thus, artificial intelligence (AI) (e.g. machine learning (ML) algorithms) were used to capture the patterns of interaction between variables (linear or nonlinear relationships).

Table 7. Regression models for prediction of the 3 outcome measures.

Deficits Models	Language age deficit		Phonological deficit		Social deficit	
	[a]MAE	R^2	MAE	R^2	MAE	R^2
Random Forest	**8.95**	0.69	**5.51**	0.2	8.89	0.25
Simple Linear Regression	11.05	0.5	6.0	−0.1	**8.29**	0.48
Gaussian Processes	10.4	0.63	6.55	−0.13	8.72	0.37
K-Star	9.56	0.62	5.61	0.2	11.63	−0.28
REP Tree	10.36	0.63	5.77	0.02	9.37	0

Indicator [a]MAE refers to Mean Absolute Error, mentioned in the methods section, Equation 5.

4.2. Artificial intelligence

Though the literature is deficient in predictive models for paediatric CI outcome, a recent cohort addressed the predictive models for cochlear implant outcomes in adults [23]. In the current study; we applied *Catboost ML model* to the whole (45 preoperative variables), 23 variables were found to influence the outcome deficits, and were arranged from the most important to the least important. Before we proceeded to creating the predictive models, we had to apply a class balancer filter, because phonological, and social deficits' classes were largely imbalanced.

Current study's classification ML models for language age deficit showed that SMO-SVM model performed better than other models (accuracy: 56%), because SVM is effective in cases where the number of variables is greater than the number of cases. *Adaboost* is one of the boosting algorithms that combine multiple low accuracy models to create a high accuracy model. Thus, it improved the accuracy because it implement ensemble learning. This is consistent with other studies which have found these ensemble-based models to provide the strongest predictive performance without a need to manually select features [24].

In the phonological deficit classification models, IBK- KNN model performed better than other models (accuracy: 88%), because it can learn non-linear functions, simple and intuitive. Social deficit classification models showed the least accuracy among other two measures, and this is may be owed to the subjectivity of social measures and the differences in the socioeconomic background of the children plus the small sample size. In addition, hearing is not the only factor that determines the social capabilities of a child and perhaps it is not the most significant factor in this domain.

Though, simple logistic classifier performed better than other models in predicting the social deficit with accuracy: 40.5%.

Five different regression ML models were used in the current study to predict the deficits in months. Random Forest (RF) model showed the least MAE and best R^2 (8.95, and 0.69 respectively) among other models used for prediction of language age deficit, and this shows much improvement in the predictive power rather than conventional statistics, in which R^2 scored 0.41. In phonological deficit regression models, there was no much difference between conventional statistical methods and artificial intelligence as regarding R^2 score, but still the presence of MAE metric gives the upper hand to the AI models. On the other hand, social deficit R^2 score was much way better using Simple Linear Regression model (0.48) as compared to (0.26) using traditional statistics.

5. Conclusions

This work demonstrated new post CI performance measures; language age deficit, phonological deficit, and social deficit, and succeeded in creating a framework for predictive scores for CI outcome deficits using ML. Traditional statistical methods succeeded in expressing the descriptive data, and linear correlations, but failed in creating reliable predictive scores for the deficit outcomes.

Although the ML classification models' accuracy for language age deficit and social deficit was less than 70% (indicating a high error rate and less reliable predictions), it can be enhanced by obtaining more data allowing for more model learning, as the more data, the more accurate the prediction. We also consider this work as an initial and crucial step in the CI field, hoping it would help in objective decision making regarding CI candidacy selection. Added value for each individual child can be assessed by calculating scores pre- and post-rehabilitation. The proposed software is being under preparation for a trial version of these predictive scores.

Acknowledgment

The authors report there are no competing interests to declare.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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