International Journal of Speech Technology (2022) 25:343–353
https://doi.org/10.1007/s10772-021-09921-0

Smart assistance to dyslexia students using artificial intelligence based augmentative alternative communication

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Received: 16 March 2021 / Accepted: 4 October 2021 / Published online: 24 November 2021
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Abstract
Dyslexia students frequently deal with multiple difficulties in daily life, involving social interactions throughout their lives. Sometimes they are quickly refused the chance to indulge in social events since they suffer difficulty in learning, reading, understanding, etc. AAC seems to be a vital communication aid for dyslexia students by providing an augmented reality (AR) paradigm to effective learning. This paper enhances the existing learning assistance technologies with innovative Artificial Intelligence (AI) to reinvigorate the Augmentative Alternative Communication (A^2C) model for dyslexia children. The AI-based Augmentative Alternative Communication Approach has been developed to enhance learning skills with dyslexia by adapting to practices, and learning models are cognitively considered. The work on the academic skills of dyslexia students has been improved through the AI-based alternative communication paradigm for the improvement of the students with reading and learning. The AI-based AAC (AI–A^2C) integrates the hybrid AI classifier in AAC to classify unique questions and provide users with the most appropriate pictograms. In contrast to the standard application, the proposed classifier decreased the effort and time taken to interact by 36.56% and 66.34%. Furthermore, the proposed model's performance is evaluated by its accuracy and efficiency of the hybrid AI classifier and compared with other AI classifiers.

Keywords Artificial Intelligence · Augmentative Alternative Communication (AAC) · Classifiers · Dyslexia

1 Introduction

Dyslexia impacts children's specific number and leads to much poorer learning and reading abilities since reading skills are essential to school success and later to employment (Giannouli & Banou, 2020; Lv et al., 2020). Dyslexic students in schools face trouble with learning and reading abilities and poor achievement levels in many social life areas (Bhattacharya et al., 2020). However, dyslexia doesn't mean that these students don't have the opportunity to learn properly; it takes them even longer and needs more effort than normal students (Papanastasiou et al., 2018). The most promising way to help dyslexic students improve their reading abilities with their usual peer group. Direct support from the teachers for dyslexic students is limited (Ji et al., 2020; Kadry & Roufayel, 2017). This can be resolved with the help of Artificial Intelligence (AI) based E-Learning methods. Such an approach must be sensitive to the learning skills and existing emotional circumstances, particularly for dyslexic children. This includes a highly adaptive learning and reading support system (Ikeshita, 2020; Sanchez-Gordon, 2020).

AI technology plays an important role in improving the teaching and learning experience, and it has become more essential in recent years (Ullah et al., 2020). AI-based E-learning has become a crucial platform for dyslexic students' to enhance their abilities and comprehension, and the internet has become a popular instructional tool for education (Baglama et al., 2018; Zhang et al., 2019). With the currently available technology that has significantly influenced the instructor's ability to deliver the curriculum, dyslexic students are frequently ignored when designing and delivering those resources (Tanwar et al., 2019). Therefore, they didn't get the same learning opportunities as regular students. The currently available E-learning resources are commonly developed based on satisfying the regular students' capabilities and needs (Shankar et al., 2021; Tiron & Gherguţ, 2019). E-learning content in its modern form

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is not assistance but rather an obstacle to the learning of dyslexic students because the tools do not take specific support in reading and learning abilities to dyslexia students, and they feel additional difficulties and drawbacks (Basheer et al., 2019). However, dyslexia studies in many ways do not have specific information about transition rules, for example, how to deal with the specific error profile in the reading and learning aspects of a dyslexic student (Prathik et al., 2018). Figure 1 details the closed-loop strategy to gather specific information on transition rules.

The first step is to interpret the adaptation information based on cutting-edge dyslexia hypotheses (Manickam et al., 2017; Sravankumar et al., 2019). Dyslexia professionals will then determine the effects of the implementation of delivering instructional guidance to dyslexia students. This assessment modifies the hypotheses of dyslexia, which are the basis for developing reading and learning assistance for dyslexia students (Manogaran et al., 2020). For such assessment loops, the adaptive behavior must be described so that untrained dyslexia professionals can quickly interrupt and alter (Chelkowski et al., 2019; Manogaran et al., 2020).

The classification of unstructured and structured data has been considered a significant challenge in the present education system. Here, the AI-based Augmentative Alternative Communication model identifies structured and non-structured data. Therefore, the latter term is used to differentiate the organized and unstructured data from data sets for dyslexia students. This model of decision-making is used to classify and increase the precision of the source data.

The remainder of this research is structured as follows. Section 2 details the relevant works. Section 3 outlines the proposed AI-based Augmentative Alternative Communication (A^2C) model. Section 4 details the hybrid AI-based classifier. Section 5 discusses the results obtained from the experimental study, and Sect. 6 concludes this study.

2 Related works

To achieve certain dyslexia training models that take both pedagogical and technical aspects into account, a simple and successful technique is proposed by Armstrong and Gutica (2020). The method suggested is used to identify primary school students' instructional patterns with recognition of dyslexia (Rose & Shevlin, 2020).

Barua (2020) deployed the tactile stimulation system based on Wepman's test to improve children's sensory discrimination with developing dyslexia in therapy sessions and provide vibrational signals to their left palms and fingers playing with each phrase of the child (Usman & Muniyandi, 2020).

Opie (2018) proved that the implementation of PMSP96 was able to replicate normal readability effects and generated the form of frequency/ consequential connections and regularisation mistakes characteristic of surface dyslexia

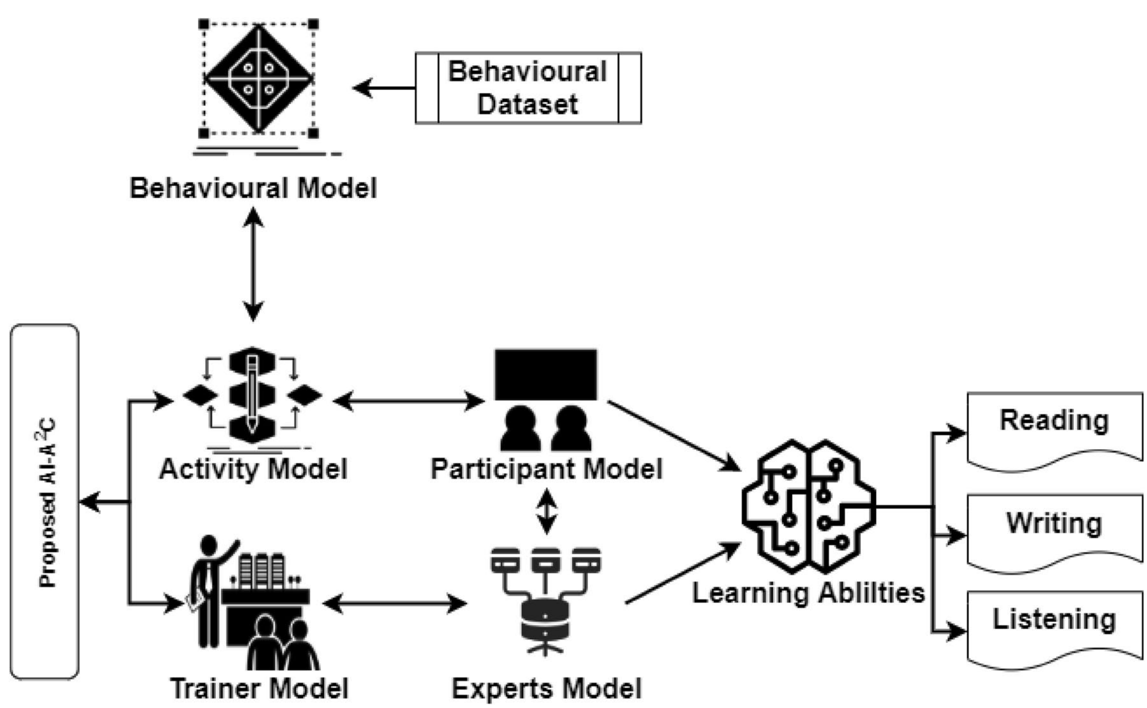

Fig. 1 Proposed AI–A^2C Model

when impaired by eliminating the semanticized input to the phonology.

Stauter et al. (2019) investigated the challenges in phonological processing that lead to processing acoustic signals for speech rhythm. Children use speech rhythms through languages to break the language into words and syllables. Distress in phonology may lead, in development, to early problems in perceiving auditory sensory signals at speech and prosody (Schneps et al., 2019). McNicholl et al. (2019) explored the existence and potential fundamental foundations of any spectrum between the disorders.

Karapetsas et al. (2019) concluded the effects of neuropsychological studies and computational modeling highlights the role of concentration in natural visuospatial perception and offers a hybrid view of careful selection for both early and late selection properties.

Ascari et al. (2018) studied the exogenous treatment of dyslexic children and the controls combined by evaluating R.T.s to cure visual cues. Xiang et al. (2021) analyzed teachers' attitudes to dyslexia and their impact on teacher standards and students' academic success with dyslexia compared with students without learning impairments.

Khamparia et al. (2020) studied visual fluency concerning administration, grammar, and phonological processing. They analyzed the productivity of reading skills in 42 students in higher education, 16 of whom had developed dyslexia, and 26 usually had lecture growth (Shankar & Jaisankar, 2018).

Xiao et al. (2020) explored that fast temporal processing is the key concern of readers with dyslexia who displayed a poorer outcome when stimuli are introduced fast rather than slowly and do well when no time components are involved.

Samuel et al. (2018) suggested that learning material suited their dyslexia form, that students were more committed and pleased with their learning. Also, adjusting the research content, according to dyslexia, will increase students' happiness and motivation.

Jones et al. (2018) explored that students who have adopted a microworld game console can reduce their cognitive load, strengthen academic performance to gains insight into uniqueness, improve their personality to promote interpersonal skills, self-efficacy and improve learning performance compared with conventional learning technology.

AI-driven AAC is the classic Shannon communications device paradigm, which includes an information source corresponding to the recipient who generates several communications messages (e.g. a series of image communication signals entered with screen touches); an internet cloud chain as a means to data transmission, a transmitter transmitting an input message to a digital delivery signal. These challenges have been resolved using the proposed technique.

Unfortunately, although these diverse frameworks have proved effective in promoting e-learning performance, they remain incapable of providing individualized experience to dyslexic learners who can be utilized in tandem with helpful technology (Chirvasiu & Simion-Blândă, 2018). This paper enhances the existing learning assistance technologies with innovative Artificial Intelligence (AI) to reinvigorate the Augmentative Alternative Communication model for dyslexia children. The AI-based AAC (AI–A^{2}C) integrates the hybrid AI classifier in AAC to classify unique questions and provide users with the most appropriate pictograms.

3 Proposed AI–A^{2}C

To improve students' learning abilities with dyslexia by adapting to the practice and teaching models that both cognitively and commitment consider, the AI-based Augmentative Alternative Communication model developed. The work focuses on dyslexia students learning abilities. In Fig. 1, the process of AI-based Augmentative Alternative Communication model for enhancing the reading and learning abilities of dyslexia students is illustrated.

In certain aspects of society, dyslexic children encounter difficulty in learning and reading and low performance. However, dyslexia does not mean that these students can learn correctly; it takes longer and requires more effort than average students.

As demonstrated in Fig. 1, the proposed model consists of five primary components: the activity model, behavioural model, participant model, experts model, and trainer model. However, the discussion on the behavioural model paradigm reflecting student interaction in reading and learning abilities. The collected information is first observed, classified, and then differentiated for delivering optimized responses for the dyslexia students. The responses are known as the recommendations based on the perceived data sources. The advice is made accessible to the relevant details in the reading and learning abilities of dyslexia students. In this method, A^{2}C is built to manage the network's non-structured data and ensure a consistent user recommendation. AI implements the classification utilizing the marginal classification system of the structured and non-structured data from the unit. The differentiation of the structured and non-structured is predicted in the following Eq. (1)

$$\beta = \frac{1}{e_o} \times \left(\frac{\mu}{e_p + o_f} \right) + \sum_{w_b} \left(d_j \times \frac{l'}{c_j} \right) + u' \times \left({w_f - w'}/{\mu} \right) - j_f \tag{1}$$

The differentiation of source data is done by evaluating the above Eq. (1), this identification is termed as μ, here the data transfer is carried out between the devices, and it is expressed as l'. The structured and non-structured data is identified, and it is denoted as w_f and w', the transferred data is identified as e_p and the number of source data is termed as e_o. The communication is established between the devices, and it is termed as $\left(d_j \times \frac{l'}{c_j}\right)$, in this identification coefficient is denoted as c_j. Different source data is expressed in the AI environment for the varying source data from the dyslexia students' learning datasets.

First-order differentiation of source data is referred to as β, where the processing time is considered to transfer the data between the source datasets and delivers the approval. The processing time is denoted as j_f, data transfer is termed as d_j. Here the history of mapping is established, using the observed data from dyslexia students learning datasets and referred to as o_f. Based on the mapping history μ' of source data, the structured and non-structured data are identified by deploying an AI-based Augmentative Alternative Communication model. Thus, the above expression is utilized to distinguish the structured and non-structured data from the dyslexia students learning datasets. This decision-making model is deployed to identify the source data and improve accuracy.

The suggested model includes five main elements: the movement model, the behavioral model, the participant model, the expert model, and the teacher model. The discussion of the compartmental model framework reflects the engagement of students in reading and learning skills. To provide optimal responses to dyslexia pupils, the collected material is first observed, identified, and then separated. The answers are referred to as advice depending on the data sources perceived. The guidance is available to children with dyslexia with their reading and writing skills.

3.1 Recommendation for dyslexia students reading and learning abilities

The proposed model for AI-based AAC systems, which is based on a sound basis of the Augmentative Alternative Communication study model and practice shown in Fig. 2. AI-based AAC is an application of cloud communications but must operationalize the vital aspects of an AAC system carefully and must concentrate on individual dynamic connectivity needs.

AI-based AAC is an inheritance of the classic Shannon communication device paradigm, which includes an information source that corresponds with a recipient who generates a series of messages (e.g. a sequence of image communication signals, entered by screen touches); a transmitter that translates an input message to a digital signal for delivery, an Internet cloud channel as a means of data transfer, the receiver that is an application that rebuilds the input from a signal in a language that the receiving user can recognize, and the direction through which the message is sent. A conceptual noise source is also available that is analogous to errors in encoding, decoding, and transmitting. The following expression is utilized to evaluate the recommendation system for the proposed model

$$\vartheta(c_j) = \prod_{s_p}^{s'} l' + \left[w_b(e_p) \times \left(\mu + \frac{\beta}{u'} \right) \right] + \left(\frac{w_f - w'/j_f}{e_p} \right) \times \sum_{j=1}^{n} d_j(j_f) + u' \tag{2}$$

The recommendation model is expressed in the above Eq. (2); in this system, the mapping history of transfer data is considered to model the recommendation model. In this work, dyslexia students learning datasets is utilized for the recommendation model that holds data mapping history, both in structured and non-structured data. The

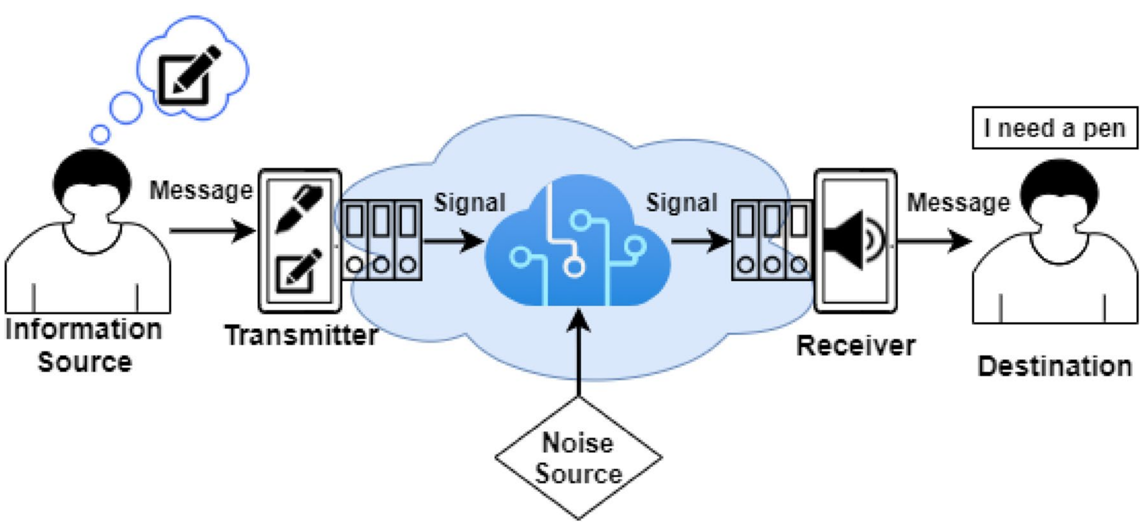

Fig. 2 Augmentative alternative communication study model

recommendation model outcome is established as the feedback to the end-user for the varying data expressed as $w_b(e_p) \times \left(\mu + \frac{\beta}{u'}\right)$. The data transmission is established for the varying source data w_b That relates to AI technology and identifies the traffic in the cloud network. The input and outcome is denoted as s_p and s', here, the recommendation is established to the dyslexia students in well advance. E-learning is based on the key forum for enhancing the skills and understanding of dyslexic pupils, and the internet is now a common educational tool. With new technologies, dyslexic students are underestimated when developing and delivering these tools and the willingness of a teacher to deliver the programme. They did not have the same chances for learning as normal students. The e-learning services available today are generally built around meeting the strengths and needs of everyday students.

4 Hybrid AI classifier

The goal of the hybrid AI classifier is to decide on a rough pictogram classification (pictogram p). The forecast is based on the time pattern of several earlier classifications. It may be due to improvements in the disposition of dyslexia students learning abilities such as reading ability and writing ability or both.

Figure 3 details the hybrid AI classifier expressed in two axis (d_1 and d_2), where the hybrid fine-tuning steps are detailed. Various AI classifiers like Maximum Entropy (ME), Support Vector Machines (SVM), Complement Naive Bayes (CNB), and Naive Bayes (NB) utilized at various points in this data space due to the model differentiation among multimodel pictograms. The model trend of different AI data classifiers $\left(D^{(p-1)}, D^{(p-2)}, \ldots, D^{(p-M)}\right)$ is initially used to predict a suitable data classifier $\left(D^{(P)*}\right)$ for the rough pictogram (pictogram p), and it is adopted for hybrid AI-based fine-tuning to obtain the updated data classifier $\left(D^{(P)}\right)$. This recommendation model is represented for mapping experience of transmission data, which is considered in this scheme as a model for the model of recommendation. In this work, dyslexia students studying databases are employed for the recommendation model that holds data mapping background, both in structured and non-structured data. The result of the recommendation model is determined as the end-user input for different data.

Due to smooth class data transformations over time, the above aspect contributes to comparatively slow improvements. The realization of a major transforming feature uses the first transforming component to collect the entire temporal pattern and remove context effects. As shown in Fig. 4, prior classifiers' maximum time dynamics are reported by the first principal component path. Initially, the analysis of facts on adaptation is focused on advanced theories on dyslexia. Professionals with dyslexia will then assess the impact of providing training advice to students with dyslexia. This evaluation modifies dyslexia theories to develop reading and learning support for students with dyslexia.

With the following sequence, the hybrid AI classifier prognosis is observed. First of all, the prior classification schemes are centralized in the classification parameter domain, as shown in Fig. 4.

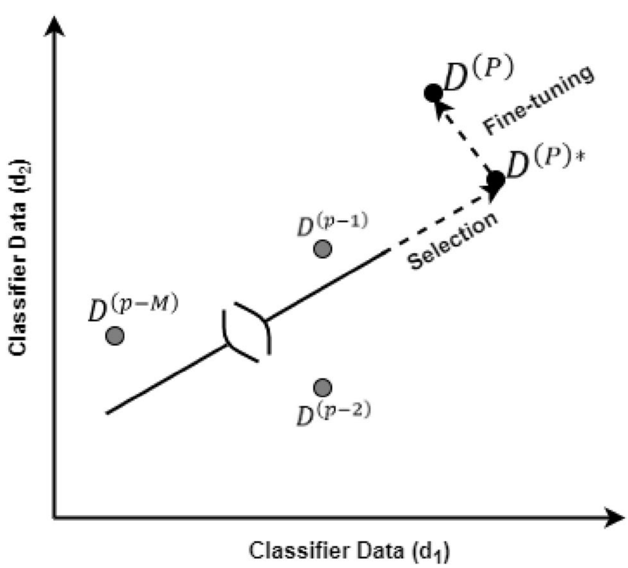

Fig. 3 Hybrid AI classifier

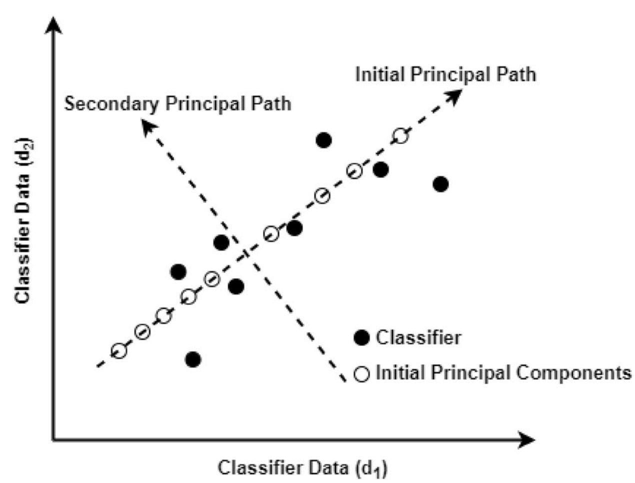

Fig. 4 Principal component analysis in the hybrid AI classifier

$$\overline{D}^{(j)} = D^{(j)} - \frac{1}{m}\sum_{i=(p-1)}^{(p-m)} D^{(i)}, \quad j = (p-1), (p-2), \ldots, (p-m) \tag{3}$$

In the above Eq. (3), $D^{(j)}$ denotes the data before domain centralization and $\overline{D}^{(j)}$ denotes the data after domain centralization of the data classifiers. A significant component transformation from classification parameter space to main component space is used to transform the domain-centered classifiers expressed in Eq. (4).

$$\overline{f}^{(j)} = H\overline{D}^{(j)}, \quad j = (p-1), (p-2), \ldots, (p-m) \tag{4}$$

where $\overline{f}^{(j)} = \left(\overline{f}_1^{(j)}, \overline{f}_2^{(j)}, \ldots, \overline{f}_n^{(j)}\right)^T$ expressed as transformed data classifier with $\overline{f}_1^{(j)}$ Denotes the initial principal data, and H denotes the matrix which provides the coefficients of transformation. The matrix H is evaluated by disintegrating the matrix $\overline{D} = \left(\overline{d}^{(p-1)}\overline{d}^{(p-2)} \ldots \overline{d}^{(p-m)}\right)^T$. With singular disintegrating value. The next step is to map on a time scale the maximum time dynamics of previous classifications. The initial principal data after the matrix transformation, $\overline{f}_1^{(p-1)}, \overline{f}_1^{(p-2)}, \ldots, \overline{f}_1^{(p-m)}$, are now integrated with the pictogram sensing data $e^{(p-1)}, e^{(p-2)}, \ldots, e^{(p-m)}$, to express the data intervals between pictogram collection, which can be non-structured. Regression analysis is applied to find a classifier for pictogram p. The selected polynomial function is expressed in Eq. (5)

$$\overline{f}_1^{(j)} = b_0 + b_1 e^{(j)} + \cdots + b_s\left(e^{(j)}\right)^s \\ j = (p-1), (p-2), \ldots, (p-m) \tag{5}$$

where s denoted as function order and $b_0, b_1, \ldots, b_m$ denoted as coefficients of fitting function. The measuring dates used are numerical days from a standard reference date. According to the structure of the sequential trend of classification, the order of the fitting feature is targetable. Higher orders of polynomials may be implemented to obtain better match precisions, but there is also an elevated chance of overfitting. Therefore, the balance between fits precision and overfitting problems should be considered when determining the fitting function.

After identifying the coefficients of fitting function b_0 and b_1 with the previous AI classifier data, the initial principal data of the selected classifier for pictograms p, $\overline{f}_1^{(p)*}$ as calculated in Eq. (6)

$$\overline{f}_1^{(p)*} = b_0 \tag{6}$$

The other principal data $\overline{f}_2^{(p)*}, \overline{f}_3^{(p)*}, \ldots, \overline{f}_m^{(p)*}$ it is fixed to zero. To get in the initial classifier parameter space, the classifier's projection is reversed from the principal component transform, followed by a domain decentralization, as shown in Eq. (7).

$$D^{(P)*} = H^{-1}\overline{f}_1^{(p)*} + \frac{1}{m}\sum_{i=(p-1)}^{(p-m)} D^{(i)} \tag{7}$$

4.1 Fine-tuning of hybrid AI classifier

The second stage of the proposed AI-based AAC systems consists of a domain adaptation algorithm. It boosts the classifier with training samples of the real image to a projected location (pictograms p). Classification estimation errors are supposed to be compensated after fine-tuning.

The algorithm is built-in advance to place the accurate classifier not far from the expected location. This is a rational assumption because the classifier prediction is based on historical data from previous images, and adjustments are always incremental over time. The goal of the finish is to improve the precision of the classification of the training samples in pictograms p. The inputs of the expected classifier and the training samples are thus integrated with the algorithm and are balanced, as detailed below. The predicted classifier uses previously limiting the fine-tuned classifier to abandon the predicted location too far. The distance between $D^{(j)}$ and $\overline{D}^{(j)}$ is minimized.

$$-\delta_i \le d_i^{(p)} - d_i^{(p)*} \le \delta_i \tag{8}$$

In the above Eq. (8), non-negative surplus terms $\delta = \left[\delta_i\right]_{i=1}^n$ are introduced to restricts the deviation of lower specification and upper specification limits of $d_i^{(p)}$ and $d_i^{(p)*}$. The information given in the current pictogram training samples (pictograms p) is used to consider the classification error of the fine-tuned classification on the samples $\left\{u_j, v_j\right\}_{j=1}^m$, where u_j denotes a vector of the sample and v_j Denotes label. To manage non-structured data non-negative surplus terms $\varphi = \left[\varphi_i\right]_{i=1}^n$ are used to allow hybrid fine-tuning classification.

$$v_j\left(\sum_{i=1}^n d_i^{(p)} u_{j,k} + d_{n+1}^{(p)}\right) \ge \varphi_i \tag{9}$$

In above Eq. (9), $u_{j,k}$ expressed as kth term of u_j. Bt integrating Eqs. (8) and (9), the optimization model can be developed and expressed in Eq. (10)

$$\min \frac{1}{2}\sum_{i=1}^n \left(d_i^{(p)}\right)^2 + D\sum_{j=1}^m \varphi_j + G\sum_{i=1}^n \delta_i \tag{10}$$

The first concept of the objective function is the margin of the classifier. The term is intended to change the separating hyperplane to a location where the maximum range of class space is generated, like that in standard SVM. The 2nd and 3rd terms are intended to mitigate the degree of violations. The optimistic parameters D and G are normalization parameters and are used to regulate weights of second-and third-term. D and G values are respectively controlled by the inputs from experiments and previous images. It should be remembered that for the fine-tuning algorithm, the parameters G and D must be preset. Classification accuracy with a grid search is the optimal combination of G and D. Lagrangian function (L_F) of the proposed model as expressed in Eq. (11)

$$L_F = \frac{1}{2}\sum_{i=1}^{n}\left(d_i^{(p)}\right)^2 + D\sum_{j=1}^{m}\varphi_j + G\sum_{i=1}^{n}\delta_i - \sum_{j=1}^{m}\rho_j - \sum_{j=1}^{m}\sigma_j\varphi_j - \sum_{i=1}^{n}\omega_i - \sum_{i=1}^{n}\varepsilon_i\delta_i \tag{11}$$

where $\sum_{j=1}^{m}\rho_j$, $\sum_{j=1}^{m}\sigma_j$, $\sum_{j=1}^{m}\omega_j$ and $\sum_{i=1}^{n}\varepsilon_i$ are multipliers of Lagrangian function. By equating derivatives of the Lagrangian function to zero respect to $d_i^{(p)}$, φ_j and δ_i. After finding ρ_j, σ_j, ω_j and ε_i the data for the hybrid AI-based fine-tuned classified model $d_j^{(p)}$ Can be obtained in the Eq. (12).

$$d_j^{(p)} = \sum_{j=1}^{m}\rho_j u_j v_j + \sigma_j - \omega_j + \varepsilon_j \tag{12}$$

The classification varies for effort and time taken to interact for D and G normalization parameters. The effort and time have taken show low to the high value that deploys the number of dyslexia students datasets. For 10 datasets, the classification process shows lesser, whereas, for 20, it defines the higher if the classification increases the effort and time taken decreases.

5 Results and discussion

In the results and discussion, data is organized based on the detection. The data collection is completed based on the conjunction with the synchronization point. The synchronization is determined when the interaction is established consistently. The equipment and the synchronization figures are concerned in this process. A processing history mapping using the data and transmitting the responses is used to make the recommendation process possible.

This section discusses the performance of the proposed AI–A^{2}C using an experimental study. In this study, the dyslexia students learning abilities are used for providing recommendations to the users. A set of 20 dyslexia students datasets are accounted for in this study for 15 unique questionnaire surveys and 75 appropriate pictograms. The survey data is observed from school and college students affected with dyslexia. With this data, the metrics accuracy, efficiency, effort, and response time are analyzed. For a comparative analysis, the existing AI-based ME, SVM, CNB, and NB classification algorithms are studied.

5.1 Accuracy analysis

The accuracy for the proposed model increases for varying survey and analysing the pictograms. The data is observed from the dyslexia students datasets, and it is performed in the AI environment to enhance the accuracy of the proposed model. Initially, the differentiation has been made between structured and non-structured data, and it is expressed as $\left(w_f - w'/\mu\right) - j_f$. Here, the identification is carried out for the varying data acquired from the dyslexia students datasets. The request is given from the sender's side, and the response is forwarded on time. The recommendation system is used to provide uniform data from AI devices. In this, the communication is established promptly and forwards the recommendation to the requested devices. Here, the structured and non-structured data are separated that deploys better detection for the varying data. The accuracy is calculated by identifying the various data on time and finds the non-structured data. If the path and the structured data are identified on time, the proposed work's accuracy increases. Thus, the accuracy increases for the varying survey and analyzing the pictograms, as shown in Figs. 5 and 6.

5.2 Efficiency analysis

The proposed model's efficiency varies for the survey and analysing the pictograms performed in the AI environment, as shown in Figs. 7 and 8. If the proper communication

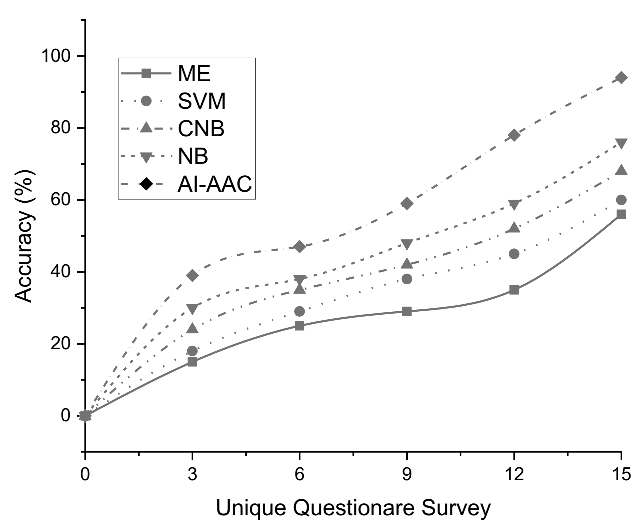

Fig. 5 Accuracy analysis (unique questionnaire survey)

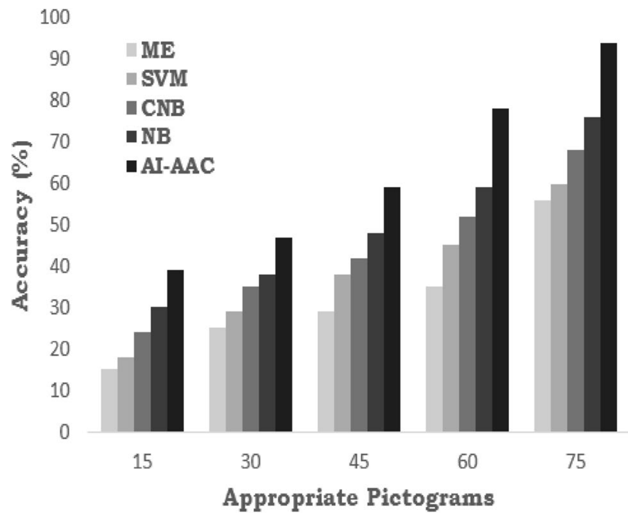

Fig. 6 Accuracy analysis (appropriate pictograms)

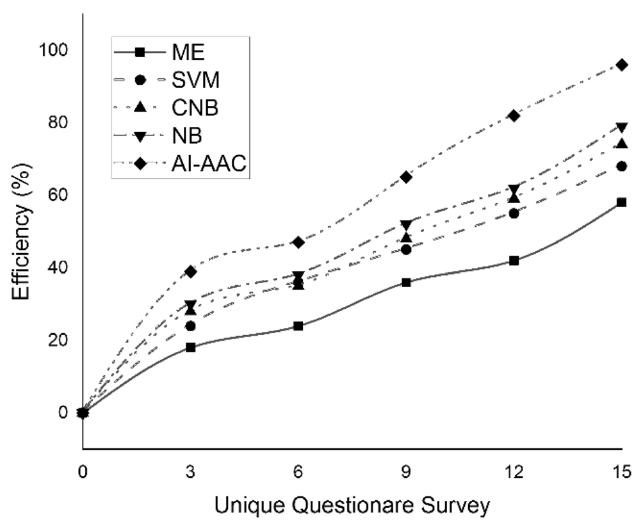

Fig. 7 Efficiency analysis (unique questionnaire survey)

developed between the teacher and dyslexia students, then the efficiency of the proposed model improved, and it is represented as $w_b\left(e_p\right) \times \left(\mu + \frac{\beta}{u'}\right)$. The mapping history is related to the verification and the submission of previous results. The structured and non-structured data contribute to the enhancement of route and bandwidth in this assessment phase. The organized data detection deploys the recommendation by mapping the previous data. The data collection correlated with the synchronization stage is performed here. If contact is formed consistently, the synchronization is calculated. This phase concerns the decision, the equipment needed, and the synchronization figures. A mapping with processing history using the data and forwarding the response is used to render the recommendation process. The

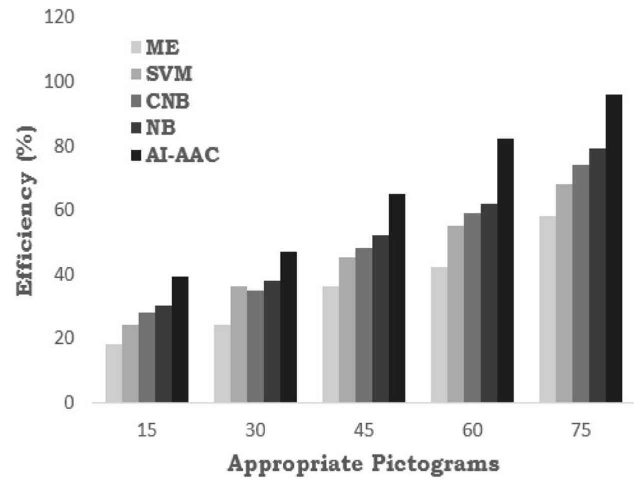

Fig. 8 Efficiency analysis (appropriate pictograms)

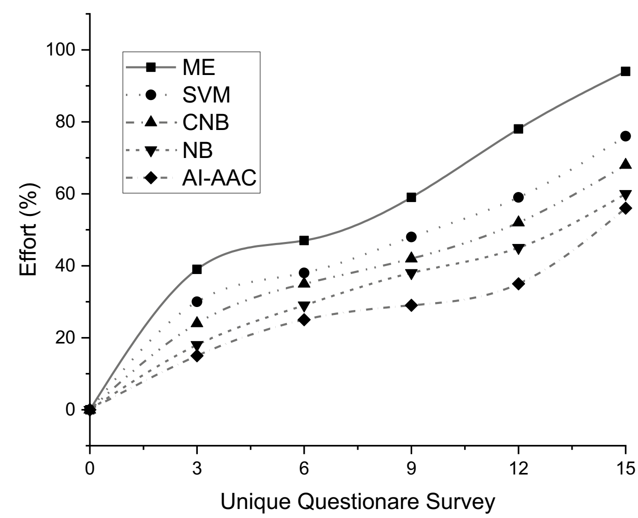

Fig. 9 Effort analysis (unique questionnaire survey)

suggestion loss happens if the mapping is not performed correctly.

5.3 Effort analysis

Figures 9 and 10 show the effort is associated with the communication established between the teacher and dyslexia students. Effort varies for the survey and analysing the pictograms; here, the selection of data points is estimated, and it is represented as $\left\{u_j, v_j\right\}_{j=1}^{m}$. The recommendation is provided to the structured data. The synchronization is then reliably resolved as the recommendation is forwarded. The loss is observed in conjunction with the collection of hyperplane and data mapping. Both uniform or not based on this recommendation, data recognition is given on a timely basis.

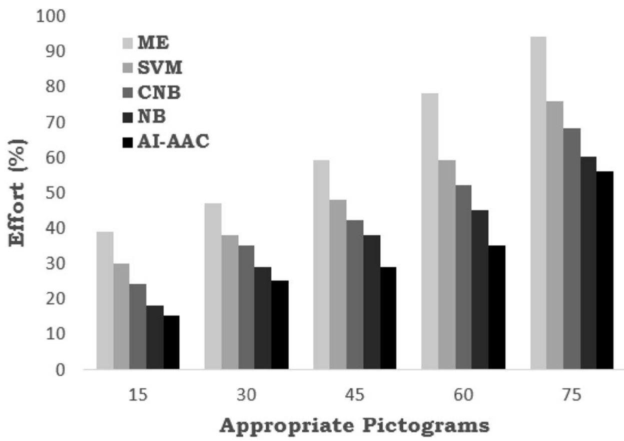

Fig. 10 Effort analysis (appropriate pictograms)

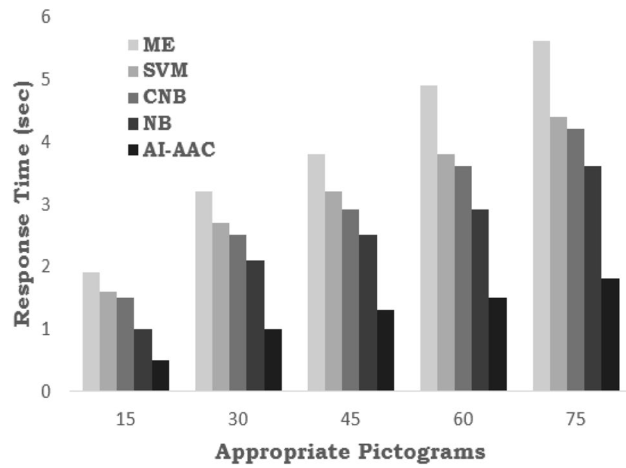

Fig. 12 Response time (appropriate pictograms)

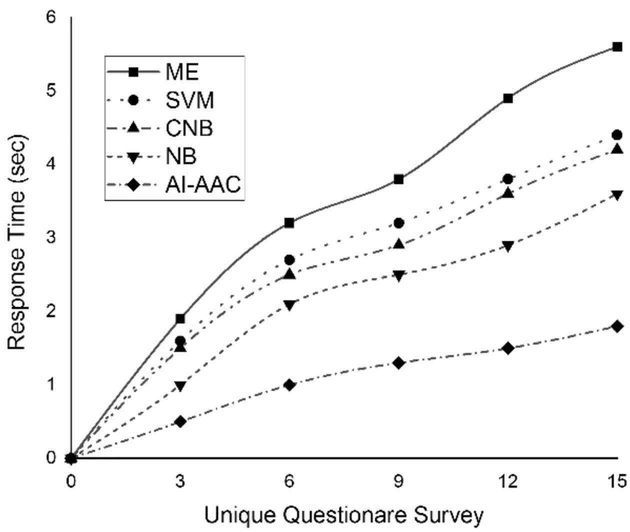

Fig. 11 Response time (unique questionnaire survey)

Table 1 Comparison results for unique questionnaire survey

Metrics	ME	SVM	CNB	NB	AI–A^{2}C
Accuracy (%)	56.15	60.18	68.93	76.45	94.98
Efficiency (%)	58.45	68.93	74.01	79.38	96.95
Effort (%)	94.93	76.15	68.43	60.25	56.48
Response time (s)	5.61	4.42	4.28	3.69	1.89

Table 2 Comparison results for analysing the appropriate pictograms

Metrics	ME	SVM	CNB	NB	AI–A^{2}C
Accuracy (%)	59.74	63.77	72.52	80.04	98.57
Efficiency (%)	61.04	71.52	76.6	81.97	99.54
Effort (%)	97.52	78.74	71.02	62.84	59.07
Response time (s)	6.35	5.21	5.02	3.89	2.11

The commitment is minimized because the submission includes uniform data obtained from dyslexia students' data sets. The assessment phase is related to the data points that detect various data. Here, the response to secure contact between the teacher and students will be forwarded on time. In this case, the monitor and bandwidth of the various data are minimized. The separating process achieves this. Data synchronization is calculated to deploy the organized data and to define fault tolerance. The data points are used to decrease the effort of the proposed model.

5.4 Response time

The response time decreases for the varying survey and analyzing the pictograms between the teacher and dyslexia students, as shown in Figs. 11 and 12. The time of responding is identified for the request from the devices that relates to the structured data. In this case, the margin is chosen to classify the data points, and interpretation is made by grouping. In the case of failure of the decision, the response time for the proposed model is decreased, and it is represented as $\min \frac{1}{2} \sum_{i=1}^{N} \left(d_i^{(p)} \right)^2 + D \sum_{j=1}^{M} \varphi_j + G \sum_{i=1}^{n} \delta_i$ This is done for the different sensor data utilized for structured and unstructured data classification. In the collection of marginal data points, connectivity between devices is created. The hyperplane determines the fault tolerance and senses the margin of this work. The collection of margins relates the data similar to the structured data. The rest of the data is known as non-structured data and is calculated on a timely basis. The recommendation is sent to the equipment demanded and correlated with data differentiation. This differentiation is used for the study of structured and unstructured data information. The comparison results are listed in Tables 1 and 2.

From the above Table 1, the proposed model (AI-A^{2}C) increases accuracy and efficiency 40.88% and 39.71% respectively and minimize the effort and response time to interact by 36.56% and 66.34% respectively.

From the above Table 2, the proposed model (AI–A^{2}C) increases accuracy and efficiency 39.39% and 38.67%, respectively and minimizes the effort and response time to interact by 43.25% and 66.77%, respectively.

6 Conclusion

In this paper, the use of an AI-based Augmentative Alternative Communication was explored to advance assistive learning tools that complement the needs and skills of students with dyslexia. The research types of students with dyslexia and the application of help technology concern these learning behaviours. AI-based e-learning framework may be created to match the services available with the student's instructional needs and abilities, which offers the degree of modification necessary to ensure that the e-learning programme incorporates the supporting tools needed to deliver student-specific learning experiences. The outcomes show that the work on the educational skills of dyslexia students has been enhanced through the AI-based alternative communication paradigm for the improvement of the students with reading and learning. This means that a wide spectrum of consumers and spectators can reused and employ the proposed model. The suggested model may be used for a range of reasons and applied to people suffering from general accessibility issues as the problems of dyslexia are also often faced by persons with other particular needs.

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