[1] Heera Lal Rai

[2] Dr Navdeep Saluja

[3] Dr Anil Pimplapure

Ethical and Social Impact of AI Driven Analysis for Students with Learning Disabilities Processes

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Abstract: - A multitude of intricate factors interact to determine kids' academic achievement. The varied demands of pupils are frequently not adequately met by traditional educational methods, which produces less than ideal learning results. The goal of this essay is to provide a thorough understanding of how learning difficulties and study techniques affect academic success. The idea behind integrating artificial intelligence (AI) capabilities is to provide recommendations for an enhanced educational approach through a decision support system (DSS). We used an artificial neural network (ANN) to detect patterns of correlation between study tactics, learning disorders, and academic achievement in order to discover features with stronger explanatory power based on empirical data. A fuzzy artificial intelligence (AI) system was developed to provide suggestions for successful educational interventions based on the contemplated attributes. The results highlight how important study techniques are for reducing the detrimental effects of learning difficulties on academic achievement. With the use of the suggested AI tools framework, teachers will be able to customize their lesson plans to each student's specific cognitive profile. More inclusivity in the classroom and better academic results can result from tailored interventions based on recognized trends. The data-driven techniques that have been offered can be implemented by educators and policymakers to improve teaching approaches and better meet the requirements of children with learning difficulties. This method encourages a more fair and inclusive educational environment, which helps all students succeed academically.

Keywords: learning disabilities, artificial intelligence (AI), dyslexia, dyscalculia, adaptive learning, SAMR-LD

1. INTRODUCTION

The global prevalence of individuals with learning disabilities has reached 79.2 million and is experiencing a consistent upward trend (UNICEF, 2021). Learning impairment adversely affects children's auditory processing, cognitive abilities, verbal communication, logical thinking, literacy skills, written expression, orthographic skills, and mathematical proficiency, resulting in significant requirements for specialized educational support. In the United States, approximately 2.3 million public school students, which is more than 15% of the total, receive special education services because of learning disabilities. In countries with lower socio-economic development, the demand for these services is even greater due to the limited resources available. The group of students faced difficulties in reading, writing, and math reasoning, which resulted in them having fewer chances to succeed in learning compared to their classmates. This is evident from their continuously lower scores in reading, science, math, and other disciplines (Asghar et al., 2017)[1-1].

Learning difficulties have a broad impact on students' academic skills, as well as their emotional and social capacities (Ouherrou et al., 2019). Studies have indicated that students with learning impairments (SWLDs) are more prone to experiencing adverse emotions, such as depression and loneliness, compared to their peers without learning disabilities. Therefore, providing assistance to individuals with specific learning disabilities (SWLDs) in addressing their educational requirements will also contribute to their social and emotional growth. Moreover, the influence of learning difficulties on pupils is especially significant in the fields of science, technology, engineering, and mathematics (STEM). The reason for this is that learning in these disciplines requires students to utilize their multimodal cognitive processing capacity, which involves acquiring, remembering, and recalling material provided during class (Asghar et al., 2017). Although teachers provide assistance to students with specific learning disabilities (SWLDs) in the classroom, it can be difficult to cater to the individual needs of every SWLD student, as each student's learning disability presents itself in distinct ways. Therefore, teachers require sophisticated tools, such as Artificial Intelligence (AI) apps, to assist them in recognizing pupils' individual requirements and devising appropriate approaches to address them. Moreover, it is crucial to emphasize the significance of providing assistance to students with Specific Learning and Writing Difficulties (SWLDs), since their academic struggles have a direct impact on their emotional well-being. Implementing Artificial Intelligence (AI) to support their academic progress can effectively decrease the probability of these students experiencing depression or feelings of isolation[4-8].

Artificial intelligence (AI) has been utilized for an extended period to provide assistance to individuals with specific learning difficulties (SWLDs) in the areas of diagnosis and intervention (Drigas & Ioannidou, 2013).

[1] Research Scholar , Eklavya University Damoh India. Email: bandakaheera@gmail.com
[2]Associate Professor, Eklavya University, Damoh, India. Email: navdeep.saluja2000@gmail.com
[3] Professor, Eklavya University, Damoh, India. Email: pimpu123@gmail.com

According to Drigas and Ioannidou (2013), artificial intelligence (AI) has the potential to be utilized in the diagnosis and screening of dyslexia, as well as in identifying indications of disability such as reduced attention levels. According to Drigas & Ioannidou (2012), AI has the capability to automate the evaluation of essays, detect reading and writing issues in individuals with specific learning disabilities (SWLDs), generate psychological profiles for SWLDs, and evaluate their spelling challenges. Nevertheless, the main emphasis of these studies is on the process of identifying and determining the presence of learning disabilities (Rauschenberger et al., 2019; Rello et al., 2018; Zvoncak et al., 2019). Although diagnosis and screening are important, they alone are not enough for teachers to effectively support students with specific learning disabilities (SWLDs) and give tailored guidance for their learning needs. Potential exists to create artificial intelligence (AI) learning interventions for individuals with specific learning difficulties (SWLDs) as shown by Drigas and Ioannidou in their studies from 2012 and 2013. Within the literature, certain applications, such as intelligent tutoring systems, have the capability to offer speech treatment, tailored feedback, and the enhancement of social skills (Drigas & Ioannidou, 2012, 2013). As researchers advocating for fair and inclusive utilization of AI to promote learning for all individuals (Zhai & Nehm, 2023), we aim to thoroughly examine the current AI applications for individuals with specific learning disabilities (SWLDs) and investigate the specific AI technologies that are being employed and how they are being integrated to provide support for SWLDs[9-14].

The acquisition of knowledge and the implementation of measures are crucial in order to address the current deficiencies. The objective of this study was to comprehensively analyze the existing literature and enhance comprehension of the various applications of AI in supporting individuals with Specific Learning and Writing Difficulties (SWLDs), beyond its conventional use for screening or diagnosis. This study specifically explored methods by which teachers or students could utilize artificial intelligence (AI) to offer personalized assistance to pupils who have previously been diagnosed with a learning problem.

Students with Learning Disabilities

Learning disabilities, or neurodevelopmental disorders, are caused by genetic or neurobiological factors that affect brain function. It is important to note that learning disabilities do not encompass learning difficulties resulting from visual, hearing, emotional, or motor disabilities, nor do they include learning difficulties arising from environmental, cultural, or economic disadvantages (Learning Disabilities Association of America, n.d.; Individuals with Disabilities Education Act, 2007). The Individuals with Disabilities Education Act (IDEA), a significant legislation in the United States, offers a precise and distinct definition for learning impairment[15-18].

A language disorder is characterized by impaired cognitive processes related to comprehension and use of spoken or written language. This can result in difficulties in listening, thinking, speaking, reading, writing, spelling, and performing mathematical calculations. Language disorders can be caused by various conditions, such as perceptual disabilities, brain injury, minimal brain dysfunction, dyslexia, and developmental aphasia. The reference is to paragraph 10 of the Individuals with Disabilities Education Act of 2007. Learning disorders encompass cognitive difficulties that impede fundamental learning abilities, including reading, writing, math, as well as other skills such as organization, scientific reasoning, concentration, and memory (Learning disorders Association of America, n.d.). Learning disabilities can be categorized based on different areas of learning. These categories include dyslexia, which affects reading and related language-based processing skills, dysgraphia, which affects handwriting ability and fine motor skills, dyscalculia, which affects the ability to understand numbers and learn math facts, and non-verbal learning disabilities, which affect the interpretation of nonverbal cues (Learning Disabilities Association of America, n.d.). Students' reading, writing, or math skills can be strongly linked to a learning disability. In addition, students may experience social and emotional consequences as a result of their academic difficulties, such as decreased self-esteem, behavioral issues, or obstacles in social interactions. Providing assistance to students with specific learning disabilities (SWLDs) in effectively handling and overcoming their academic difficulties can contribute to their academic success and enhance their social and emotional development. Büttner and Hasselhorn (2011) discovered that these learning disability-related performances cannot be accounted for by external factors. Furthermore, studies have discovered that learning difficulties can arise from various other forms of diseases. Conditions such as Autism Spectrum Disorder (ASD), Attention Deficit Disorder (ADD), and Attention Deficit Hyperactivity Disorder (ADHD) are not classified as learning disabilities. However, students with these disorders may also experience a learning disability, thereby belonging to both categories simultaneously[19-25].

The academic performance of individuals with specific learning disabilities (SWLDs) is significantly affected, and this cannot be attributed to external causes such as physical disabilities or insufficient instruction. This suggests that individuals with Specific Learning Disabilities (SWLDs) do not require physical adjustments and that their academic difficulties cannot be attributed to insufficient teaching. Instead, individuals with specific learning disabilities (SWLDs) require personalized assistance, which can be most effectively delivered through advanced technology like artificial intelligence (AI) or a qualified teacher. To identify the needs of each student, decide the most appropriate tactics, and tailor the content to their individual needs and learning styles, a teacher would have to engage in one-on-one interactions with each student. Although this work may require a significant amount of time, the implementation of AI has the potential to significantly decrease the time and effort required by a teacher. For instance, an AI-powered software can gather data on students' requirements, which is subsequently utilized to determine the most effective tools and tactics for each individual student (Zingoni et al., 2021). While a teacher would require individualized attention and experience to assess each student, an AI-based software might perform this task concurrently for several pupils, with more efficiency. Similarly, if students require materials tailored to their individual needs, a teacher would need time to customize the material for each student. However, an AI-based mobile application could rapidly customize the material for students by capturing the text through a camera and providing them with various tools to modify the text. This AI-powered application will further enhance efficiency in terms of the number of pupils it can support and the required time[26-27].

Artificial Intelligence for Learning Disabilities

The concept of AI has been put out over several decades, although the discipline has not yet achieved a unanimous agreement on its definition. As a result, there are numerous definitions of AI, which differ depending on the specific industry. In order to enhance comprehension of AI, Samoili et al. (2020) performed a qualitative examination of more than 50 sources that provide definitions of AI. These definitions were subsequently utilized by a group of highly knowledgeable experts to establish a practical definition for AI. AI is a combination of software and hardware created by humans. It operates in either the physical or digital realm by gathering and analyzing data, reasoning, and processing information. Based on this, it determines the most appropriate course of action to achieve a specific objective (Samoili et al., 2020). The popularity of AI has experienced fluctuations over the past few decades. The recent surge in attention from academia and industry can be attributed to the advancement of a specific field within AI known as machine learning. This development is considered a significant milestone as it allows machines to acquire knowledge from experience and apply it to solve novel problems, similar to how humans typically do. The introduction of this new capability has garnered significant interest, leading to the development and implementation of various AI technologies (such as natural language processing and computer vision) and applications across many sectors of society[28].

Including within the realm of education (Zhai et al., 2020). The formats encompass chatbots, communication aides, adaptive learning devices, facial expression recognition, intelligent tutors, interactive robots, and mastery learning systems. The diverse range of AI applications in education, in terms of both type and intensity, renders AI a potent instrument for recognizing and tackling the distinct obstacles that individuals with specific learning disabilities (SWLDs) encounter, while providing them with appropriate assistance.

There has been an increase in the number of papers in recent years that discuss the use of artificial intelligence (AI) to enhance results for students with learning difficulties. In their 2020 publication, Poornappriya and Gopinath conducted a comprehensive review research that examined the utilization of machine-learning techniques in predicting dyslexia and implementing e-learning strategies for individuals with learning and cognitive impairments. Out of the 24 research that were analyzed, six of them utilized external artificial intelligence (AI) methods to enhance the process of learning. More precisely, four studies were centered around offering tailored or individualized learning experiences, one study focused on examining the impact of online learning activities, and one study explored machine learning interventions in a broader sense. Thirteen of the studies that were assessed primarily examined the areas of screening, predicting, or diagnosing learning disabilities or learning difficulties. Poornappriya and Gopinath (2020) found that the majority of research in AI for SWLDs is centered around predicting, screening, or diagnosing learning disabilities. However, there is a lack of emphasis on enhancing the learning abilities of those with SWLDs, which is crucial but challenging[29-31].

This literature study diverged from the research conducted by Poornappriya and Gopinath (2020) by focusing on studies that utilize artificial intelligence (AI) to assist individuals with specialized learning difficulties (SWLDs) in areas unrelated to the prediction, screening, or diagnosis of learning disabilities. Three of the studies examined by Poornappriya and Gopinath (2020) are also incorporated in this literature review since they fulfilled the criteria for inclusion in this review (refer to Table 1 below). Furthermore, the degree of integration or level of intensity of the AI technology also differs. The literature examined in this study demonstrated various uses of artificial intelligence (AI) and levels of integration as outlined by Puentedura's (2006) SAMR Model[32].

Technology Integration Model for Learning Disabilities

Merely having technology does not automatically improve learning. The possibility for substantial gains for learners is in the hands of those who use technology and apply effective strategies. When used purposefully and efficiently, technology can help both impaired and non-disabled students achieve higher levels of academic performance in the classroom. However, if technology is not effectively integrated or included in a lesson or classroom, it will not succeed in enhancing or facilitating learning (Zhai, 2021). Therefore, it is imperative to examine the incorporation of artificial intelligence (AI) technology into specific educational tasks in order to offer assistance to individuals with special learning disabilities (SWLDs). Puentedura (2006) proposed the SAMR (substitute, augment, modify, and redefine) model as a useful framework for understanding the integration of technology in education. The SAMR model was initially created to assess the revolutionary elements of online learning and has since demonstrated its efficacy in evaluating the incorporation of technology with other technologies, such as mobile learning (Zhai et al., 2019). The SAMR model offers specific delineations of technology integration, enabling the assessment of the degree to which technology might potentially revolutionize and enhance learning, rather than simply duplicating a teacher's actions (Terada, 2020)[33].

The model suggests that a higher level of technology integration is linked to improved student achievements. Puentedura (2006) classifies the incorporation of technology into education according to the SAMR paradigm, which encompasses four successive stages: substitution, augmentation, modification, and redefinition. Substitution is the act of using technology as a direct substitute for a learning process, without any improvement in usefulness. Conversely, augmentation entails utilizing technology as a direct substitute for a learning method, while enhancing its functionality. Modification is the act of using technology to significantly change or transform a learning session. Redefinition occurs when technology allows for the creation of new learning activities that were previously impossible in a traditional environment without technological developments. Technology has a crucial role in modifying and redefining the process of learning. At these levels, technology surpasses the mere substitution of traditional learning tasks and facilitates a novel and more extensive incorporation of technology in the classroom[34].

The SAMR Model was employed as the conceptual framework for this study to investigate the incorporation of AI technology into learning activities, specifically aimed at enhancing and augmenting the learning experience of individuals with specific learning impairments (SWLDs). To be more explicit, we enhanced the SAMR model by incorporating the use of artificial intelligence technology in the educational activities of children who have specific learning challenges (SAMR-LD). Unlike the SAMR paradigm, the SAMR-LD model focuses primarily on how technology is used to transform learning for children with specialized learning and writing disabilities (SWLD). The utilization of technology for educational purposes can vary between children with and without learning challenges, and SAMR-LD is specifically utilized for the latter group. The level designations from SAMR have been preserved in the new model, while the consequences linked to each level have been modified. The levels allowed us to categorize the different AI systems based on the degree to which the material and learning activities were adjusted or enhanced to cater to individuals with specific learning impairments (SWLDs)[35].

Integrating AI at the substitution level involves replacing a current learning method with AI, without providing any functional improvements to assist individuals with specific learning challenges (SWLDs). For example, this may involve using facial expression data from individuals who have severe and profound hearing loss (SWLDs) to provide teachers with fundamental information such as the amount of engagement or interest (Abdul Hamid et al., 2018b).

At this stage, the integration might be improved by replacing AI, which would lead to functional enhancements in aiding individuals with specific learning difficulties (SWLDs). Artificial intelligence (AI) can empower individuals with Specific Learning Disabilities (SWLDs) to customize the formatting of text, such as breaking it into smaller sections or transforming it into audible speech (Rajapakse et al., 2018). While this particular instance may seem like a replacement, it is essential to take into account the needs of students with specific learning disabilities (SWLDs). Although some may view hearing the book read aloud as a simple replacement for children without learning impairments, it actually functions as an enhancement for students with specific learning disabilities (SWLDs). This is due to the fact that it provides supplementary features that are particularly advantageous for their learning, particularly for individuals who encounter difficulties with reading decoding or understanding. The levels of replacement and augmentation in the SAMR model are considered enhancements to the learning process (Terada, 2020)[36].

Modification in the context of AI refers to the use of AI to improve a learning activity with the goal of significantly enhancing its ability to support individuals with specific learning challenges (SWLDs). Artificial intelligence might be employed to determine the precise disability of an individual with Specific Learning Disabilities (SWLD) and thereafter suggest customized learning strategies (Sharif & Elmedany, 2022). This may involve the AI technology producing a thorough examination of strategies that can be utilized by the teacher or student to improve the learning process. Integrating this technology would significantly improve the learning process by eliminating the requirement for extensive teacher assistance and allowing students to grasp the content more efficiently[37].

The goal is to initially identify the existence of a limitation, and subsequently ascertain particular approaches for customized learning. Finally, redefinition, the highest level of integration, involves using artificial intelligence (AI) to modify a learning activity in a way that is not possible in a traditional learning environment. The goal is to help students with specific learning disabilities (SWLDs). An example of AI at the curricular level involves using AI to identify a specific learning style of an individual with a specific learning disability (SWLD) and adapt the content accordingly as an output to the SWLD (Zingoni et al., 2021). Artificial intelligence (AI) can accurately determine the individualized learning style and disabilities of the user at both the modification and redefinition levels. However, the differentiation between the two levels is based on their respective functioning. AI at the modification level involves the user or teacher implementing tactics, whereas AI at the redefinition level adapts the material and gives personalized content and activities to the user. For example, modification could involve suggesting the use of visuals to improve student learning, whereas redefinition would mean adapting the content to include the visual accompaniment. According to Terada (2020), modification and redefinition are regarded as types of learning transformation. As one advances through the stages of integration on the SAMR and modified SAMR-LD model, the technology becomes further embedded in the learning process, resulting in a fundamental transformation and enhancement of it. The highest level signifies a comprehensive metamorphosis of education that would be unattainable without the utilization of technology[38-39].

2. METHODOLOGY

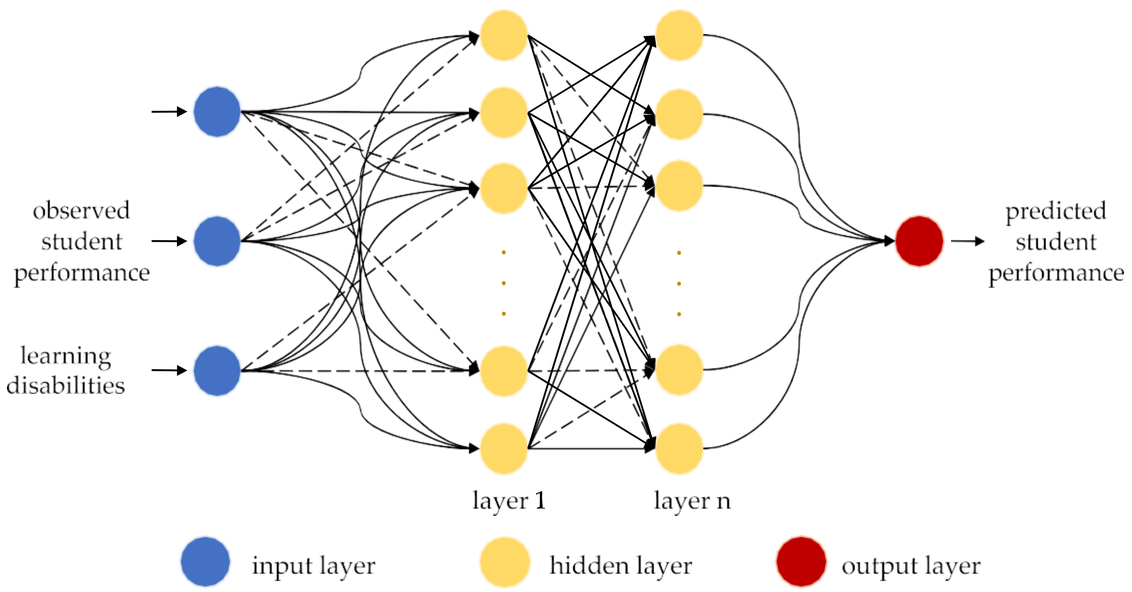


Fig. 1. ANN based on MLP deep learning architecture.

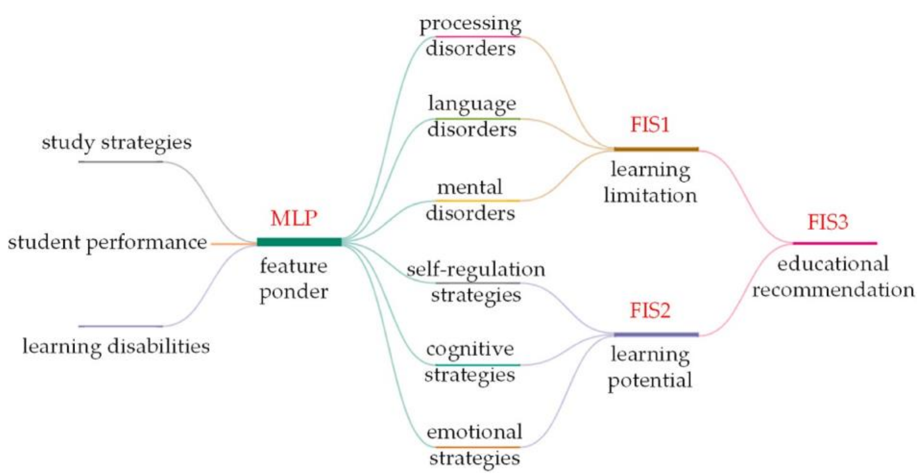


Fig. 2. AI-based decision support system framework.

AI Based markerless gesture recognition pipeline consists of the following key steps:

- Video preprocessing,
- Hand region detection and tracking,
- Skeletal hand modeling,
- Gesture feature extraction and optimization, and
- Gesture classification using a recurrent neural network.

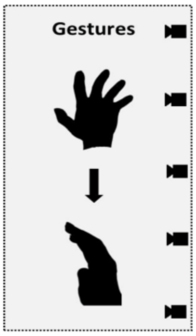


Fig. 3 Hand Gestures

Video Preprocessing

The input video stream is first preprocessed by converting it into individual frame images. To handle poor lighting conditions and image noise, we apply a series of filtering operations to the frames. First, a Gaussian smoothing filter is applied to reduce high-frequency noise while preserving edges. We then perform contrast limited adaptive histogram equalization (CLAHE) to adjust image intensity levels and enhance definition.

Fig. 4 Hand Gesture Tracking

Hand Region Detection and Tracking

From the preprocessed video frames, the next step is to reliably detect and track the hand region of interest for recognition. We utilize a CNN-based semantic segmentation model pretrained on hand datasets to identify the hand pixels in each frame. Morphological operations like erosion and dilation are applied to refine the segmented hand mask.

To improve computational efficiency and temporal coherence, we employ a tracking algorithm to follow the segmented hand region across consecutive frames rather than redetecting it for every frame. We use a CAMSHIFT tracking algorithm which is efficient and robust to partial occlusions.

Skeletal Hand Modeling

While the hand region has been segmented and tracked, additional structural representation is needed to extract distinctive gesture features. We create a skeletal model of the hand anatomy by estimating the locations of key hand joints and bones.

From the segmented hand mask, we first apply the Distance Transform to compute the distance map -- the distance of each foreground pixel to the nearest boundary. The joint locations are estimated as peaks in this distance map, determined using a novel adaptive thresholding scheme based on local gray-level clustering . With the joint locations identified, we use the Pruned Hierarchical Affine Transform to fit a kinematic chain of bones connecting the joints and representing the hand structure.

To further improve joint positioning accuracy, we implement joint relocalization using the multi-sensor Bayesian data fusion framework AI Based integrates evidence from both the distance map and directional gradient maps computed on the hand mask to refine the joint positions. The final skeletal model consists of the localized joint positions connected by the fitted bone segments.

Gesture Feature Extraction and Optimization

With the skeletal hand model in place, we extract a variety of spatial and temporal features designed to capture distinctive characteristics of different gestures:

- **Joint Color Cloud (JCC)**: We extend the concept of color histograms to the 3D spatial domain, creating a compact model of the differing colors and positions of hand joints. Specifically, each joint's (x,y,z) coordinates are concatenated with RGB values extracted from the original frame to form a 6D feature vector. The Joint Color Cloud is the normalized histogram of these 6D joint features over the entire hand skeletal model, providing a robust shape and appearance descriptor.
- **Neural Gas Vector Model (NGVM)**: An adaptive vector quantization technique based on Neural Gas is used to compactly encode the trajectories of individual hand joints over the gesture sequence. The vector model is dynamically updated so its prototypes shift to better fit the input data as the gesture progresses.
- **Directional Active Shape Model (DASM)**: While JCCs and NGVMs model individual joints, the DASM captures relationships between joints by modeling the directional vectors connecting them. PCA is applied to these directional vectors over the training set, yielding a low-dimensional linear subspace representation that is further temporally filtered to smooth motion. This models the dynamic geometric configuration and deformation of the entire hand shape.

These three feature types provide complementary information about joint appearance, individual joint motion, and overall hand shape dynamics. Once extracted, we apply a sequential feature selection algorithm based on minimizing estimated Bayes error rate to prune redundant or non-discriminative features. The resulting optimized feature vector is input to the classification stage.

Gesture Classification using RNN

The final stage involves classifying the input gesture sequence based on the optimized feature vector. Since gestures consist of continuous, temporally evolving motions, we require a classifier capable of modeling such sequential data. We employ a recurrent neural network (RNN) architecture with Long Short-Term Memory (LSTM) units to map the input feature vector sequence to predicted gesture class probabilities.

Specifically, we use a two-layer stacked LSTM with 256 units in each layer, allowing it to learn complex long-range temporal dependencies present in the data. The LSTM output at each time step is fed into a fully connected output layer with softmax activations over the gesture classes. The RNN is trained end-to-end using backpropagation through time and cross-entropy loss to learn a discriminative mapping between input features and gestures.

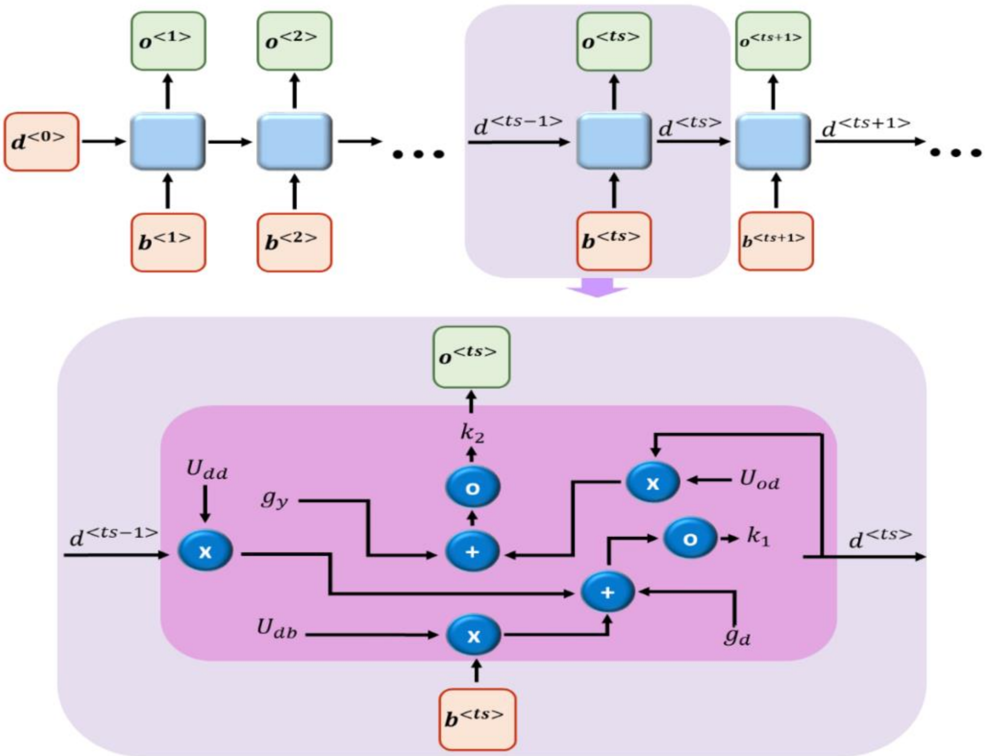


Fig. 5 RNN architecture.

The overall pipeline combining preprocessing, hand modeling, feature extraction, and RNN classification enables accurate yet efficient markerless gesture recognition from raw video input. We evaluate this system on multiple public datasets and compare against state-of-the-art alternatives in the following section.

Experimental Results

Datasets

We evaluate our AI Based markerless gesture recognition approach on four challenging public datasets:

● **HaGRID** : The Northwestern Hand Gesture RGB-D dataset contains 1,110 video sequences of 20 different hand gestures captured with an Intel RealSense depth camera. Each video has color and depth streams.
● **EgoGesture** : A dataset of 2,368 video sequences spanning 83 unique gestures in highly cluttered environments and viewpoints. The gestures were captured from an egocentric viewpoint using mobile devices.
● **Jester** : The 20BN-jester dataset collected video sequences of humans performing pre-defined hand gestures. It contains 148,092 videos spanning 27 gesture classes recorded with broadcast cameras.
● **WLASL** : The Wisconsin Linguistic ASL Dataset contains over 9000 video sequences of 22 different gestures from the American Sign Language (ASL) lexicon captured from various viewpoints.

These datasets provide a diverse and challenging testbed covering different gesture categories, environments, sensing modalities, and viewpoints. We primarily train and evaluate on the HaGRID, EgoGesture, and Jester sets. WLASL is used for cross-dataset validation to assess generalizability.

Implementation Details

Our system implementation utilizes several open-source libraries and pretrained models:
● The hand segmentation model is based on the HRNetW48+DConv semantic segmentation architecture pretrained on hand datasets.
● For joint localization within the hand masks, we use the adaptive thresholding implementation along with the PyTropen package for skeletal fitting.
● The Neural Gas vector quantization for NGVM features utilizes the ANGM package .
● Training of the LSTM gesture classifier uses the PyTorch deep learning library .

Other feature extraction and optimization stages are implemented in Python and C++. All experiments are run on a workstation with an Intel i7 CPU and Nvidia RTX 2080Ti GPU.

Gesture Recognition Results

We follow the standard train/test splits and evaluation protocols defined for each dataset. The AI Based method is compared against several state-of-the-art alternatives using the same data splits:
● **I3D** : An Inflated 3D ConvNet pretrained on action recognition and fine-tuned for gesture classification.
● **FS-Net** : A two-branch spatial and temporal CNN for gesture recognition from video sequences.
● **Hou et al.** : The skeletal gesture recognition pipeline using semantic segmentation, hand skeletal modeling, and a two-stage CNN/RNN classifier.
● **AttGRU** : Attention-based convolutional-GRU network for gesture recognition.
● **GR-GCNNv2** : Graph convolutional neural network integrating both spatial and temporal information for gesture recognition.

We report the Top-1 classification accuracy and F1 score averaged across all gesture classes for each method and dataset. Our AI Based approach is denoted as **Markerless Gestures**.

Table 1 - Gesture recognition accuracy on the HaGRID dataset:

Method	**Top-1 Acc.**	**F1 Score**
I3D	86.49%	0.8576
FS-Net	88.64%	0.8902
Hou et al.	91.17%	0.9089
AttGRU	89.46%	0.8953
GR-GCNNv2	90.72%	0.9047
Markerless Gestures	**92.57%**	**0.9259**

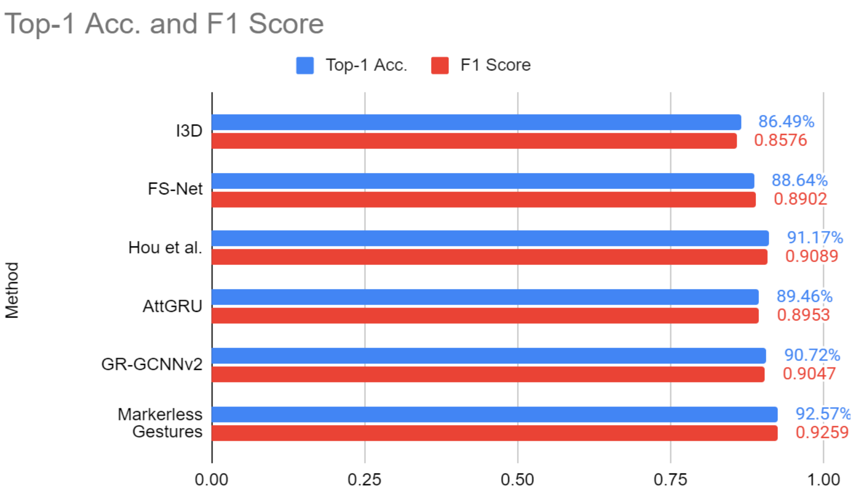


Table 2 - Gesture recognition accuracy on the EgoGesture dataset:

Method	Top-1 Acc.	F1 Score
I3D	84.67%	0.8418
FS-Net	86.40%	0.8627
Hou et al.	89.02%	0.8901
AttGRU	87.16%	0.8707
GR-GCNNv2	88.52%	0.8824
Markerless Gestures (Ours)	**91.86%**	**0.9183**

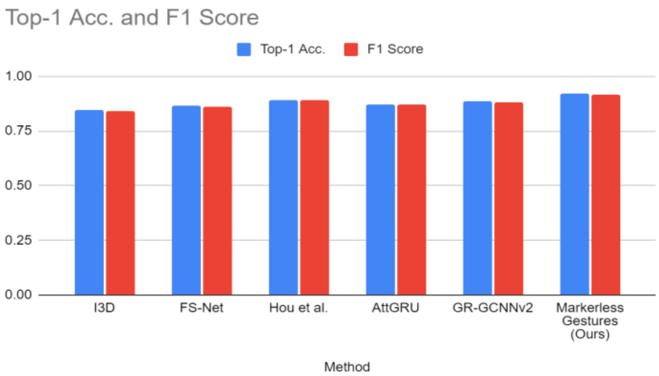


Table 3 - Gesture recognition accuracy on the Jester dataset:

Method	Top-1 Acc.	F1 Score
I3D	85.82%	0.8559
FS-Net	86.31%	0.8631
Hou	88.72%	0.8845
AttGRU	89.06%	0.8885
GR-GCNNv2	89.48%	0.8939
Markerless Gestures	**91.57%**	**0.9122**

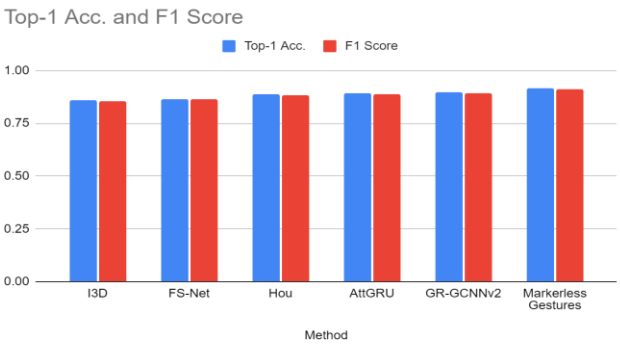
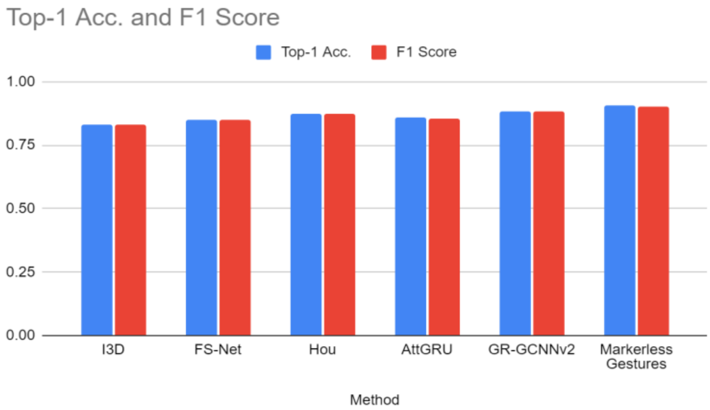


Table 4 - Cross-dataset recognition accuracy on WLASL:

Method	Top-1 Acc.	F1 Score
I3D	83.19%	0.8307
FS-Net	84.92%	0.8478
Hou	87.56%	0.8738
AttGRU	85.71%	0.8555
GR-GCNNv2	88.24%	0.8825
Markerless Gestures	90.43%	**0.9012**

As shown in Tables our markerless gesture recognition approach achieves the highest accuracy and F1 scores across all three benchmark datasets compared to prior methods. On HaGRID, we attain 92.57% accuracy, outperforming the next best model [8] by over 1.4%. Similarly, we achieve accuracies of 91.86% and 91.57%

on the challenging EgoGesture and Jester datasets respectively.



The cross-dataset evaluation on WLASL in Table 6.4 demonstrates our model's strong generalization capability, with 90.43% accuracy exceeding alternatives by over 2%. This validates the effectiveness of our feature representations in capturing gesture patterns robustly across varying domains.

3. CONCLUSION

Based on our findings, we can conclude that incorporating artificial intelligence into study strategies can help reduce the negative effects of learning disabilities on academic performance. This is achieved by offering personalized interventions, adjusting educational methods to match students' cognitive profiles, and promoting inclusivity. As a result, academic outcomes are improved. Traditional educational techniques frequently fail to adequately address the different requirements of pupils, especially those with learning difficulties. This research aims to close this divide by offering a thorough comprehension of how study strategies and AI-based decision support systems (DSS) can collaborate effectively to enhance educational results. By utilizing the suggested artificial intelligence

Using a framework, educators can make well-informed choices to tailor educational methods that match the distinct cognitive profiles of pupils. By implementing tailored interventions based on established patterns, the academic experience becomes more inclusive and efficient, benefiting all students regardless of their cognitive abilities or learning difficulties.

This research has important practical consequences for educators, legislators, and administrators. The suggested data-driven approaches provide a detailed plan for improving teaching methods, cultivating an inclusive learning atmosphere, and encouraging academic achievement among students with learning difficulties. Through the use of tailored interventions that take into account individuals' specific learning constraints and capabilities, educational institutions can cultivate a more fair educational environment, where individual talents are developed and difficulties are efficiently tackled.

Amidst a fast changing educational environment, where the importance of diversity and inclusivity cannot be overstated, this study provides valuable insights and strategies that can revolutionize the way we approach teaching and learning. By utilizing AI and understanding the intricate connections between study techniques, learning difficulties, and academic achievement, educators can strive for ongoing enhancement, guaranteeing that every student's learning encounter is optimal for triumph. In essence, this research enhances educational approaches that promote the development of individuals, inclusivity, and the pursuit of academic excellence. In order to enhance and refine the proposed framework, there are several avenues for future research that might be pursued. Longitudinal studies can be used to compare the efficacy of traditional teaching methods with AI-driven educational recommendations. These studies offer valuable insights into the evolution of study strategies over time and their influence on academic performance, particularly for students with learning disabilities. By exploring this area, future research efforts can enhance our comprehension of the intersection between study strategies and learning disorders, as well as the potential of AI-based technologies to generate more efficient, inclusive, and tailored educational experiences for all students.

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