DyGAN: Generative Adversarial Network for Reproducing Handwriting Affected by Dyspraxia

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***Abstract*—Dyspraxia primarily affects coordination and is categorized into two forms: 1) Motor, and 2) Verbal ororal. This study focuses on motor dyspraxia, which influences individuals in learning movement-related tasks. Consequently, the *DyGAN* initiative employs deep convolutional aversarial generation networks, using deep learning to create characters resembling human handwriting. The methodology in this study is structured into two main stages: 1) the creation of a first-order cybernetic model, and 2) the execution phase. Using four independent variables and three dependent variables, eight outcomes were analyzed using variance analysis. DyGAN is a twin Deep Convolutional Neural Networks and it is highly sensitive to the Learning Rate. It scored a 67% on the proposal, suggesting that characters can sound written by a human. The project will feature writers from different backgrounds and will help augment data for writing resources for dyspraxia, potentially benefiting those struggling with writing difficulties and improving our understanding of education. The model is designed to be widely applicable. Future work could customize the model to mimic the way a specific child writes, with neural networks, for example.**

Keywords*—Children with neurodevelopmental disorders; dyspraxia; generative adversarial network; deep learning; deep convolutional neural network; human handwriting

I. Introduction

Since 2020, the World Health Organization (WHO) estimates that there are 1 billion people living with some form of disability, which means that approximately 15% of the world's population has difficulties in their psychosocial functioning and frequently requires assistance services. On the other hand, in Mexico, according to data from the National Institute of Statistics and Geography (INEGI), there are 6.2 million people who have some form of disability, which represents 4.9% of the total population.The most well-known activities for types of disabilities are six: 1) Walking, climbing, or descending, 2) Seeing, 3) Hearing, 4) Speaking or communicating, 5) Remembering or concentrating, and 6) Difficulty with bathing, dressing, or eating. People with disabilities may have more than one disability.

Dyspraxia, also known as Developmental Coordination Disorder (DCD), is a condition that affects physical coordination, which can make daily tasks more challenging for children. In the school setting, children with dyspraxia often struggle with activities that require fine and gross motor skills. This can include difficulties with handwriting, cutting with scissors, participating in sports, and even simple tasks such as tying shoelaces or buttoning clothes. These challenges can cause frustration and a sense of inadequacy among affected children, as they may find themselves behind their peers in performing seemingly simple tasks [1], [2].

The academic implications of dyspraxia are significant. Children with this condition may have difficulty with tasks that require motor planning and coordination, such as writing legibly and quickly, which is essential for taking notes and completing written assignments. This can result in lower academic performance not because of lack of understanding or intelligence but due to the physical difficulties associated with the disorder. Furthermore, the effort required to complete these tasks can be exhausting, leading to decreased stamina and increased stress, which can further affect a child's ability to learn and engage in the classroom [3], [4].

Socially, children with dyspraxia often face additional hurdles. Their difficulties with coordination and motor skills can make it difficult to participate in group activities and sports, which are crucial for social development and peer relationships. These children may be perceived as clumsy or awkward, leading to possible teasing or bullying from classmates. This social isolation can have profound effects on your self-esteem and general mental health. In addition, teachers may not always be aware or understand the needs of children with dyspraxia, leading to inadequate support and accommodations in the classroom. It is crucial for educators to receive proper training to recognize and support students with dyspraxia, ensuring that they have the tools and understanding necessary to help these children thrive academically and socially [5], [6]. Then, according to Pinos-Medramno et al. in [7], the school performance of children with dyspraxia in Basic Education has a negative impact on their normal development and therefore on their learning process, particularly in their writing. Addressing these challenges requires innovative solutions, such as the application of Artificial Intelligence (AI).

Artificial intelligence can be divided into two main types: 1) AI based on its functionality and 2) AI based on capacity. For the development of a DyGAN, capacity-based AI is utilized, which is further divided into three branches:

1) Artificial Narrow Intelligence (ANI): Its function is to focus on performing a single task, but it has limited memory. At this stage, it should be prepared to act in a single role, minimizing its performance as much as possible.
2) Artificial General Intelligence (AGI): It has the ability to mimic human thinking because of its high cognitive level.
3) Artificial Super Intelligence (ASI): It is the most powerful AI, as it has the capacity for faster learning

and achieving autonomy, which allows it to replicate human behavior and even surpass human thinking ability. However, as of 2023, it is still in the development phase.

For the conceptualization and advancement of a DyGAN, Generative Adversarial Networks (GANs) are utilized due to their proficiency in synthesizing character images derived from a pre-established database, potentially curated for general-purpose applications. The deployment of GANs is notably advantageous as they comprise two neural networks that engage in a competitive dynamic, thereby facilitating the generation of highly realistic imagery. This approach enables the efficient production of a diverse array of character images, which is particularly advantageous for applications necessitating extensive visual datasets. It is imperative to underscore that, at their core, Neural Networks are employed, categorized into five principal architectures:

1) Transformer Neural Networks: These are self-aware neural networks that have been developed for text and are currently driving significant advances in natural language processing.
2) Recurrent Neural Networks: This is a type of artificial neural network that has a sequential structure or time-series data. They are used in applications such as language translation, speech recognition, and image captioning.
3) Siamese Neural Networks: Their functionality is based on the use of two conditions for evaluation. After the evaluation is performed, the output is passed to a classifier which generates the result. They are primarily used for document evaluation.
4) Convolutional Neural Networks: They have many layers, each dedicated to detecting different visual features. Filters are applied to training images with different resolutions, and the output of each layer is obtained by convolving the image, which is then used as input for the next layer.
5) Generative Adversarial Networks: Their use is to generate images from existing datasets, with one network called the generator and the other called the discriminator, competing with each other to generate new instances that resemble those in the training data distribution.

Each of these architectures has distinct characteristics and strengths, making them suitable for a variety of tasks within the domains of artificial intelligence and machine learning. Consequently, the integration of Generative Adversarial Networks (GANs) with these fundamental neural network architectures can significantly enhance the performance and capabilities of a Dynamic Generative Adversarial Network (DyGAN) in generating high-fidelity character images. This advancement facilitates various applications, including digital handwriting analysis, educational tools for children with learning disabilities, and other scenarios where the generation of realistic character images is imperative. For the development of a DyGAN, GANs are employed to generate character images from a pre-established database, which could be designed for general use.

This work is therefore divided into four additional sections. The second section provides an analysis of related work on Generative Adversarial Networks (GANs). Then, this section explains the theory surrounding GANs, including essential definitions for understanding neural networks. The third section summarizes the methodology of this proposal, so that the following section can conduct experimentation aimed at finding optimal hyperparameters to improve the results. Finally, conclusions are developed, focusing on the research findings and possible improvements or future directions that the work could take.

II. Method

The study of dyspraxia dates back to the late 19th century, with the British physician Sir William John Little being the first to study it in depth and name it as such [8]. By 1937, Samuel Orton declared it one of the six most common developmental disorders and showed a distinctive impairment of praxis. He also titled it *Reading, Writing, and Speech Problems in Children*. He was one of the first to break away from the concept of simple recovery reading and treat all aspects of language as related, doing so in a language clinic [9]. Later, in 1972, Anna Jean Ayres categorized Dyspraxia as a Sensory Integration Disorder. During this period, she wrote several books, two of which stand out: 1)S̃ensory Integration and Learning Disorders (1972) and 2)S̃ensory Integration and the Child (1979). In addition, she published multiple academic articles that addressed her theory and techniques for clinical application and founded the *Ayres Clinic*, based in Torrance, California, USA, where she evaluated and treated children using her developed approach. Sensory integration therapy emphasizes detailed evaluation, understanding the unique sensory challenges and styles of each child, which forms the basis for providing the child with appropriate learning opportunities, processing, and using sensory information to improve the child's performance skills [10].

A. Related Work

The exploration of advanced technologies for neurodivergent learning begins with the study *Exploring the Efficacy of an IoT Device as a Sensory Feedback Tool in Facilitating Learning for Neurodivergent Students* in [11]. This research investigates how IoT devices can provide real-time sensory feedback to enhance the learning experiences of neurodivergent students. These devices offer customized responses that improve engagement and learning outcomes by creating adaptive learning environments. Similarly, the *Web-based Assessment and Training Model for Dyslexia, Dyscalculia, Dysgraphia, Dyspraxia, ADHD and Autism* in [12] provides a digital platform for individualized assessments and training. The Web-based model integrates educational games and cognitive exercises, offering flexibility and scalability for diverse educational settings. Both studies underscore the potential of digital tools to support personalized and inclusive education.

Building on the theme of interactive learning technologies, the study *Improving Cognitive Learning of Children with Dyspraxia Using Selection-Based Mid-Air Gestures in the Athynos Game* [13] explores the use of Mid-Air Gestures-Based Interactions in the Athynos game to improve cognitive learning for children with dyspraxia. This approach not only engages children more effectively but also improves their cognitive and motor skills. This research aligns with *ATHYNOS: Helping Children with Dyspraxia Through an Augmented Reality Serious Game* in [14], which uses augmented reality to create interactive learning experiences targeting specific motor and cognitive skills. Both studies highlight the effectiveness of immersive and interactive technologies in supporting children with motor impairments, emphasizing the role of serious games in educational and therapeutic settings.

The advancement of computational diagnostic systems is exemplified by *TestGraphia, a Software System for the Early Diagnosis of Dysgraphia* in [15], which uses advanced algorithms to analyze handwriting and identify patterns of dysgraphia. This objective and quantifiable method aids in early diagnosis, which is critical for timely interventions. Complementing this approach is *Preventing Dyspraxia: A Project for the Creation of a Computational Diagnostic System Based on the Theory of Embodied Cognition* in [16], which leverages computational techniques to assess motor and cognitive functions, providing a holistic view of dyspraxia. Both studies emphasize the importance of early detection and intervention, using computational tools to enhance diagnostic accuracy and support effective therapeutic strategies.

The integration of wearable haptics and Virtual Reality (VR) in rehabilitation is explored in *Wearable Haptics and Immersive Virtual Reality Rehabilitation Training in Children with Neuromotor Impairments* in [17]. This study shows that combining haptic feedback with virtual reality significantly enhances the rehabilitation process by providing engaging and interactive experiences. Similarly, *Integration of Serious Games and Wearable Haptic Interfaces for Neuro Rehabilitation of Children with Movement Disorders: A Feasibility Study* in [18] examines the feasibility of using serious games and haptic interfaces for neurorehabilitation, reporting improvements in motor functions and user participation. These studies demonstrate the potential of immersive technologies to create effective rehabilitation environments for children with neuromotor impairments.

Focusing on learning disabilities, *Rotoscopy-Handwriting Prototype: Using computer animation technique to assist handwriting teaching for children with dyspraxia* in [19] and *using the rotoscopy technique to assist handwriting teaching for children with dyspraxia* in [20] both present innovative methods employing rotoscopy and computer animation to teach handwriting. These systems provide visual and kinesthetic feedback, helping children with dyspraxia improve their handwriting skills through interactive exercises. These studies highlight the value of specialized software in addressing specific educational challenges associated with learning disabilities.

The study *Puzzle Time - VR Runner* [21] presents a VR game designed to support the development of cognitive and motor skills in children. By combining cognitive puzzles with physical activities, the game encourages physical movement and cognitive engagement, making it a useful tool for educational and therapeutic purposes. This approach is echoed in *Case Study: Using a Novel Virtual Reality Computer Game for Occupational Therapy Intervention* in [22], which explores the use of a VR game for occupational therapy. The positive results in motor skills and patient participation reported in these studies underscore the potential of VR games as effective tools to enhance cognitive and motor skills.

Lastly, the application of advanced machine learning techniques is highlighted in *Integrated Transfer Learning Based on Group Sparse Bayesian Linear Discriminant Analysis for Error-Related Potential Detection* in [23]. This study uses transfer learning to improve the detection accuracy of error-related potentials in EEG data, demonstrating the utility of machine learning in neurorehabilitation settings. Additionally, *Contemporary Speech/Speaker Recognition with Speech from Impaired Vocal Apparatus* in [24] addresses the challenges of speech recognition for individuals with impaired vocal apparatus, emphasizing the importance of inclusive technologies that accommodate diverse needs. Both studies show advances in machine learning and speech recognition technologies that contribute to better diagnostic and therapeutic outcomes.

Together, these studies illustrate the significant progress that is being made in the use of advanced technologies to support neurodivergent learning and rehabilitation. From IoT devices and web-based platforms to immersive VR and specialized software, these innovations are creating more inclusive, engaging, and effective educational and therapeutic environments. Using these technologies, educators and clinicians can provide better support and interventions, ultimately improving outcomes for people with learning and developmental disorders.

B. Deep Convolutional Generative Adversarial Networks

Deep Convolutional Generative Adversarial Networks (DCGANs) constitute a particular type of neural network designed to generate data from an existing dataset as observed in Fig. 1. The primary goal of DCGANs is to examine and understand the distribution of data within the training set, with the purpose of reliably generating new data that follow this distribution [25].

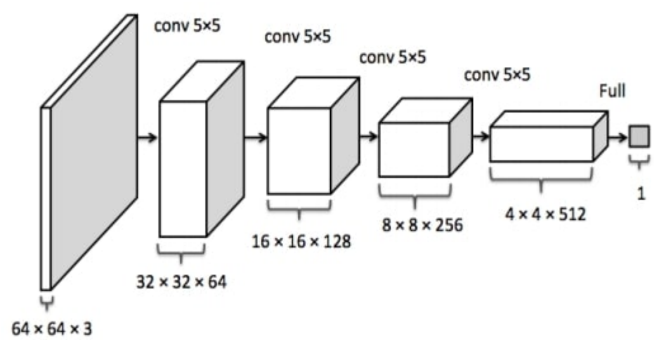

Fig. 1. Representation of Deep Convolutional Generative Adversarial Networks (DCGANs) [26].

A GAN network consists of two neural components: 1) a *Generator* (G), and 2) a *Discriminator* (D). The primary function of the generator is to understand the distribution of the training dataset and produce information that fits that distribution. On the other hand, the Discriminator evaluates the probability of authenticity of a given data point, determining whether it comes from the real training set or if it is synthetic, generated by G. Fig. 2 shows not only the architecture, but also the interaction between G and D.

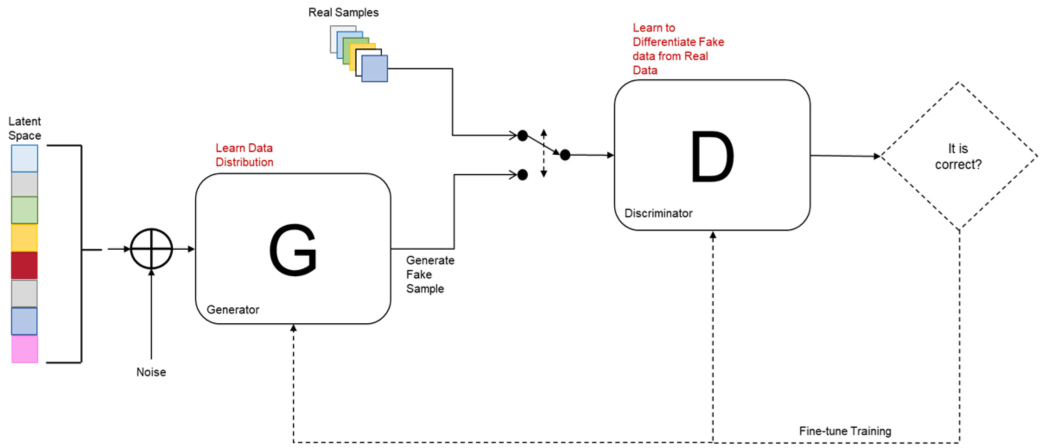

Fig. 2. Architecture of a DCGAN [27].

In this manner, **G** and **D** compete against each other through a Minimax game, where each adversary seeks to maximize its actions while simultaneously minimizing those of the opponent. The mathematical representation of this Minimax game in GANs is expressed by Eq. 1.

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z)))] \quad (1)$$

The objective is to train the discriminator **D** to accurately classify the data as authentic, maximizing $\mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)]$, or synthetic, maximizing $\mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z)))]$, where the output probability should approach zero. Concurrently, the generator **G** is optimized to deceive the discriminator **D** through the generation of data that closely resemble the training set, thus minimizing $\mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z)))]$. Within this framework, the MinMax game is engaged solely in the latter part of the equation. As Goodfellow elucidated in [28] the aforementioned equation may not provide an adequate gradient for **G** to learn effectively. This limitation arises because, during the initial phases, the data synthesized by **G** are of insufficient quality, leading **D** to reject them with high confidence, given their stark divergence from the real training data. Then Eq. 2 provides a summary of how the Generator and the Discriminator compute the gradient throughout the training process.

$$V_{\text{GAN}}(D,G) = \begin{cases} D : \max_D \mathbb{E}_{\mathbf{x}\sim p_{\text{data}}(\mathbf{x})}[\log D(\mathbf{x})] \\ +\mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}(\mathbf{z})}[\log(1-D(G(\mathbf{z})))] \\ G : \max_G \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}(\mathbf{z})}[\log(D(G(\mathbf{z})))] \end{cases} \quad (2)$$

In addition, Eq. 2 describes the objective functions for Generative Adversarial Networks, where we can identify the two main components in it: the Discriminator (D) and the Generator (G).

$$\textbf{Discriminator}(D) : \max_D \mathbb{E}_{\mathbf{x}\sim p_{\text{data}}(\mathbf{x})}[\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}(\mathbf{z})}[\log(1-D(G(\mathbf{z})))] \quad (3)$$

The Discriminator's objective is to maximize the expected value of correctly distinguishing between real data (x) from the data distribution and generated data (G(z)) from the Generator, Eq. 3. It seeks to maximize the logarithmic probability that real data are classified as real and the logarithmic probability that generated data are classified as fake.

$$\textbf{Generator}(G) : \max_G \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}(\mathbf{z})}[\log(D(G(\mathbf{z})))] \quad (4)$$

The Generator's objective is to maximize the expected value of the log probability that the Discriminator classifies the generated data as real, Eq. 4. Essentially, the Generator tries to fool the Discriminator by generating data that is indistinguishable from real data [27]. The Fig. 3 shows the mathematical interaction of the GAN components for the generation of an image or synthetic data.

C. DyGAN

In Fig. 4, the DyGAN first-order cybernetic model, an MNIST database and numbers are included. The algorithm was designed in such a way that the user enters a character and, in turn, connects to an MNIST database containing characters. In the output, the character is displayed on the screen. The system is controlled by feedback, as efficiency is important in determining whether accuracy has been achieved. This is the principle of DCGAN, which is a Deep Convolutional Generative Adversarial Network. The discriminator and the generator are involved in the process.

From Fig. 5, the Generator and Discriminator are fundamental processes that enable the functionality of DCGAN. The generator creates images from pixels, in this case, with a size of 28, which matches the one used in the MNIST database. In each epoch, the Generator produces an image and the Discriminator evaluates whether it is real or fake. If the discriminator indicates that it is fake, the process continues over several epochs until it can confuse the discriminator or match the generated images with those in the database. The following algorithm describes the training and inference process of the GAN designed for the MNIST dataset to aid children with dyspraxia. The GAN model consists of a

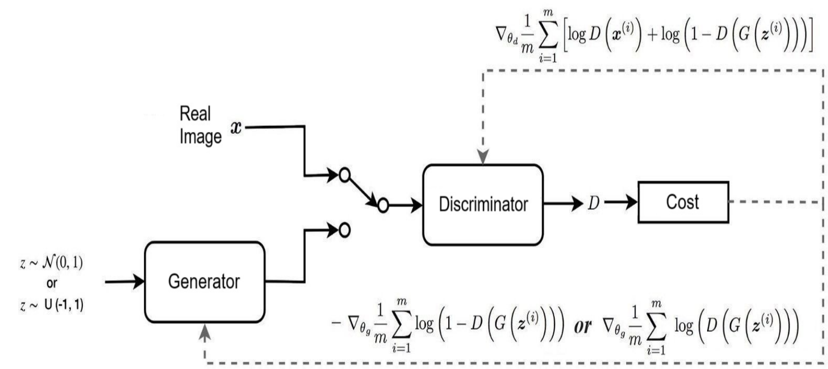

Fig. 3. Mathematical diagram of the generator and discriminator components.

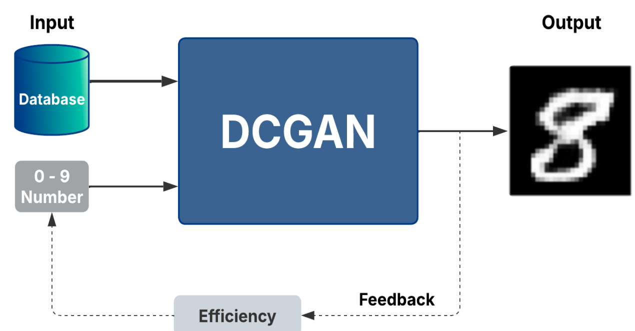

Fig. 4. DyGAN first-order cybernetic model over MNIST database, only numbers are included.

generator and a discriminator, where the generator creates new images from random noise, and the discriminator evaluates the authenticity of the images. Stages of the training and inference methodology for a GAN on MNIST to help children with dyspraxia Here we will preprocess the data and train our model followed by deployment of models.

Algorithm 1: GAN Training and Inference for MNIST

Initialize: Generator G, Discriminator D, learning rate α, batch size m **Input:** MNIST dataset X, random noise Z

Training Phase **for** *number of training iterations* **do**

Sample minibatch of m noise samples $\{z^{(1)},\ldots,z^{(m)}\}$ from noise prior $p_z(z)$ Sample minibatch of m examples $\{x^{(1)},\ldots,x^{(m)}\}$ from data distribution $p_{data}(x)$

Update Discriminator: $\theta_d \leftarrow \theta_d+\alpha\nabla_{\theta_d}\frac{1}{m}\sum_{i=1}^{m}[\log D(x^{(i)})+\log(1-D(G(z^{(i)})))]$

Update Generator: $\theta_g \leftarrow \theta_g+\alpha\nabla_{\theta_g}\frac{1}{m}\sum_{i=1}^{m}[\log D(G(z^{(i)}))]$

Inference Phase **Input:** Trained Generator G, new random noise z **Output:** Generated image $G(z)$ Sample noise z from noise prior $p_z(z)$ Generate image using G: $\hat{x}=G(z)$ **return** $\hat{x}$

Algorithm 1 provides a comprehensive description of the training and inference process. In the Training Phase, the generator and discriminator are updated iteratively. The generator G learns to create realistic images by minimizing the discriminator's ability to distinguish between real and generated images, while the discriminator D aims to maximize its accuracy in this task. In the Inference Phase, the trained generator uses new random noise z to produce new images, providing a useful tool for evaluating therapeutic progress in children with dyspraxia through generated visual aids. This methodology ensures a systematic and effective training process, facilitating the creation of high-quality synthetic data that can be utilized in therapeutic settings.

III. Experimental Results

First, since we propose three independent variables: 1) batch size, 2) learning rate, and 3) activation function, we carried out a total of eight experiments, as shown in Table I. Based on this, an Analysis of Variance (ANOVA) was performed. The analysis in an ANOVA table is associated with certain factors being investigated, including the activation function, batch size, and learning rate, along with their residuals. The Sum of Squares tells us how much variance each source contributes to the total data set. Degrees of freedom (df) refer to how many values or quantities in a statistical distribution, for every factor. The sum of squares is divided by the corresponding degrees of freedom to calculate the mean square, which measures the average variance due to each source. Thus, the F-Ratio is calculated as a ratio of mean square of source/mean square residuals to tell if its variances are significantly different. P-Value - is the probability value, and it is used to determine the significance of an observed effect. Since we can obtain four dependent variables or test variables: 1) Discriminator Loss (D Loss), 2) General Accuracy, 3) Adversarial Loss, and 4) Discriminator Accuracy (D Accuracy), we can infer the behavior of the system in four independent branches. Table I also shows the best results for each dependent variable highlighted in gray.

Table II shows that it is evident that none of the factors, activation function, batch size, or learning rate, demonstrate statistically significant effects on overall efficiency over Discriminator Loss, as indicated by their high P-values. However, it should be noted that the *Learning Rate*, although not statistically significant, has a value of P closest to zero among the

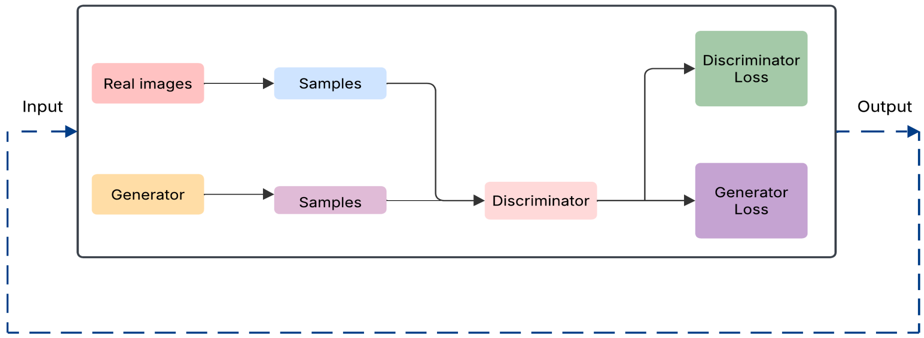

Fig. 5. DyGAN first-order cybernetic extended model over MNIST database, only numbers are included.

TABLE I. EXPERIMENTAL DESIGN BASED ON THREE INDEPENDENT VARIABLES (*italics*) WITH FOUR DEPENDENT OR OUTPUT VARIABLES (**BOLDS**)

Activation Function	*Batch Size*	*Learning Rate*	**D Loss**	**General Accuracy**	**Adversarial Loss**	**D Accuracy**
RELU	64	2e-4	0.626676	0.601562	0.623441	0.71875
RELU	64	2e-3	0.688536	0.652653	0.652653	0.59375
RELU	32	2e-4	0.684453	0.5625	0.762182	0.40625
RELU	32	2e-3	0.629332	0.671875	0.93706	0.21875
TANH	64	2e-4	0.626756	0.664062	0.897452	0.296875
TANH	64	2e-3	0.674438	0.523438	0.846442	0.234375
TANH	32	2e-4	0.583811	0.6875	0.718293	0.625
TANH	32	2e-3	0.694146	0.5625	0.791022	0.375

TABLE II. ANOVA TABLE WITH DIFFERENT SOURCES OF VARIABILITY, EFFECT OVER DISCRIMINATOR LOSS

Sources	**Sum of Squares**	**df**	**Mean Square**	**F-Ratio**	**P-Value**
A) Activation Function	0.000310578	1	0.000310578	0.17	0.7015
B) Batch Size	0.0000760391	1	0.0000760391	0.04	0.8485
C) Learning Rate	0.00339307	1	0.00339307	1.85	0.2450
Residuals	0.00732558	4	0.00183064		
Total (Corrected)	0.0111023	7			

TABLE III. ANOVA TABLE WITH DIFFERENT SOURCES OF VARIABILITY, EFFECT OVER GENERAL ACCURACY

Sources	**Sum of Squares**	**DF**	**Mean Square**	**F-Ratio**	**P-Value**
A) F.A	0.000326274	1	0.000326274	0.5	0.8286
B) Batch Size	0.000227484	1	0.000227484	0.04	0.8564
C) L.R	0.00138228	1	0.00138228	0.23	0.6592
Residuals	0.0244519	4	0.00611296		
Total(Corrected)	0.0263879	7			

three factors, making it the most significant factor compared to the activation function and batch size. This suggests that while the effects are not statistically significant in general, the Learning Rate has a relatively stronger influence on the outcome measure. From Fig. 6, we also notice that the learning rate factor (LR) is more significant when conducting the experiments, as it influences the way DyGAN learns and is a factor to consider.

The ANOVA of Table III analyzes the variability of the General Accuracy through contributions attributable to various factors. Since the Type III sum of squares has been chosen, the contribution of each factor is assessed by eliminating the effects of the other factors. The P-values indicate the statistical significance of each of these factors. Since no P-value is found to be less than 0.05, it is again concluded that none of the factors exerts a statistically significant effect on General Accuracy at a confidence level of 95%.

IV. CONCLUSIONS

We presented the Deep Convolutional Generative Adversarial Networks to lay down theoretical background for the proposal and discuss how it works, mathematically-based solutions, tools, and applications involving on it. Furthermore, a methodology for creating an application capable of producing personalized fonts with DCGANs was described. The performance of the proposed model was evaluated by ANOVA to confirm its precision. In summary, the Learning Rate is found to be one of the governing parameters affecting DyGAN. The proposal was 67% correct, which means that the possible characters may have been written by a human. This proposal is intended to contribute to the creation of dyspraxia in writing expanding resources for learning through data augmentation with potential support for those who have dyspraxia. The architecture is intended for anyone with a writing issue, and in this respect it has an obvious impact on the education building.

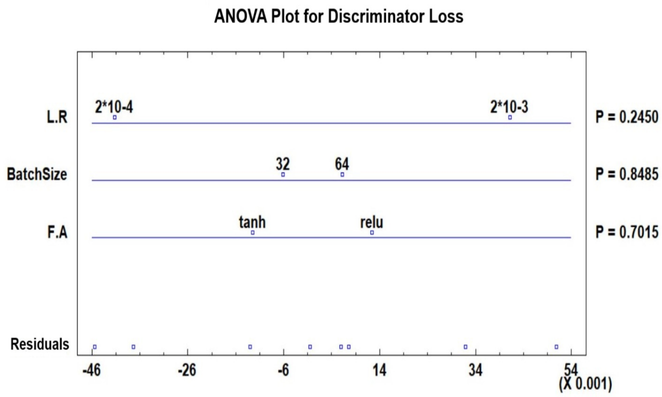

Fig. 6. Analysis of residuals on the variable discriminator loss.

Our application aims to provide a model that is deployable and that can be used effectively by all audiences. Future work for DyGAN can also be a case study to have unique characters from each person in which the model imitates handwriting of particular child, and extension with other models/architects as well including artificial neural networks.

Acknowledgment

The research described in this work was carried out at the Centro de Investigación en Computación (CIC) together with the Escuela Superior de Ingeniera Mecánica y Eléctrica (ESIME) of the Instituto Politécnico Nacional, Campus Zacatenco. It should be noted that this research is part of a degree thesis entitled *DPGAN: Aplicación de DCGAN en la generación de caracteres únicos a través de la inteligencia artificial* supported by *Jesús Sebastián Ruiz Cruz*, work directed by Dr. Jesús Jaime Moreno Escobar.

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