*Detection Of Dysgraphia Through Convolutional Neural Networks*

## Abstract

Dysgraphia is a learning disability that significantly affects an individual's ability to communicate themselves in both social and formal contexts, potentially leading to negative consequences for their mental well-being, self-assurance, and overall behavior. This condition is a neurological ailment characterized by impairments in verbal expression, written communication, and the acquisition of knowledge. The consequence of this is the development of substandard and distorted penmanship, characterized by errors in spelling and spacing. The conventional approach to addressing dysgraphia has been individualized occupational therapy sessions. However, this method can be both expensive and time-consuming, limiting its accessibility to all children in need of such therapies. Numerous scholarly investigations have been conducted to explore the identification of dysgraphia through the utilization of machine learning algorithms on a digital tablet. However, the aforementioned research utilized traditional machine learning techniques that involved human extraction and selection of features. Additionally, these algorithms were designed for binary classification tasks, specifically distinguishing between individuals with dysgraphia and those without dysgraphia, utilizing numerical data.

The objective of this report was to distinguish between handwriting of proficient students and individuals with dysgraphia by utilizing machine learning techniques. Through the application of Convolutional Neural Networks (CNN) on a dataset consisting of images, our objective was to extract complex features that enable a more thorough examination. This methodology facilitated the successful differentiation of unique patterns within handwriting styles. The analysis carried out on the training dataset shows potential for accurately identifying dysgraphia, which could result in more focused treatments and support measures for persons affected by this condition. Consequently, this has the potential to improve their overall learning experience and educational achievements.

# INTRODUCTION

1. About Dysgraphia

A neurological disorderliness that leads to deformity in expression, writing and learning. It leads to poor and deformed handwriting (Spelling and spacing). A communication and transcription disability, It is a SLD (specific learning disability) that leads to impaired and disoriented handwriting It often overlaps with other learning and neurodevelopment disorders. A learning disability that definitely impacts the forms of expression of a person in social and formal interactions and could take a toll on the person's mental health, confidence and conduct in general.

The cause of the disorder is still under the clouds but has been described as a biological- disorder related to genes and hierarchical characteristics something in correlation with working memory problem caused by neurological dysfunction. People having such disability fail to make efficient connection with different fragments of the brain. People with such disorder fail to develop a hold over their motor movements. The defect in orthographic loops, coding and graph motors. The images of the words or sentences in stockpile of the brain fail to convey the message to the eyes and fail to develop proper feedback. 6 and 15 chromosomes play a vital role in SLDs where it leads to poor interpretation of speech reading disabled and disoriented writing with lower sense of response.

There aren't any specific gold standards to actually detect such disorders on certain lab based tests neither there is a any specific medical correlations that can be generated in order to predict whether a person is suffering from such disease looking at genetics. This is likely to be observed in a person and more often it is quite evident if one is suffering from it. The brain is one of the most vital and complex organs of the body and each and every fragment and nerve has a lot to do with the basic working and conduct of a person in day-to-day life and to be very clear without challenging all the medical research that has been conducted in the past this organ still needs to be studied and explored a lot.

Children that experience difficulties in learning often necessitate a constant and specific form of guidance in order to enhance their proficiency in handwriting. The process of diagnosing such disorders during examinations can be intricate and challenging due to the presence of numerous contributing elements. The manifestation and severity of warning signs may vary depending on the child's age and stage of development. It is of utmost importance that therapies are undertaken in a simultaneous manner, particularly in cases when these symptoms endure for a duration of no less than six months.

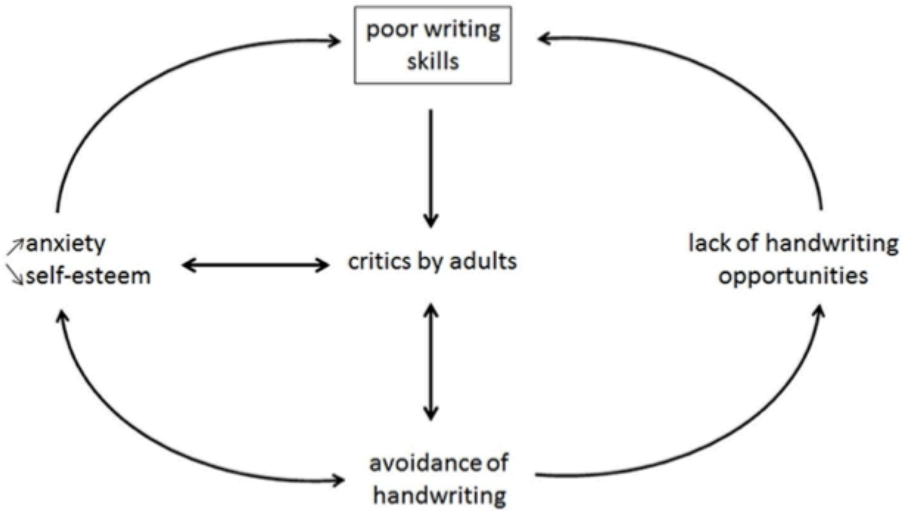


Fig 1. Vicious life circle filled by anxiety created due to the learning disorder. Adapted from [20]

Dysgraphia is a neurodevelopmental condition characterized by difficulties in writing and spelling skills. It can occur either in isolation or in conjunction with other learning problems such as dyslexia, dyscalculia, dyspraxia, and central auditory processing disorder. It is worth noting that this disease has been seen to frequently coincide with other ailments such as autism spectrum disorder and attention deficit hyperactivity disorder. Consequently, the presence of these other disorders can complicate the accurate identification and diagnosis of this condition.Dysgraphia is a complex condition that can be classified into two distinct categories: language-based and non-language-based. Language-based dysgraphia refers to difficulties that individuals experience in spelling, organizing words in a coherent sequence, and accurately transcribing their thoughts into written form. Conversely, dysgraphia that is not language-based predominantly stems from challenges in fine motor skills. In many instances, although the language processing centers in the brain function within normal parameters, the individual experiences difficulties in regulating the motor skills required for controlling hand, arm, and finger muscles in order to produce writing that is easily readable.

Although dysgraphia is primarily identified during childhood, it is not limited to this specific population. Adults can also receive a diagnosis, typically as a result of a brain damage or stroke.

Moreover, it is important to note that there are five discrete categorizations of dysgraphia, each of which has a unique impact on various aspects of the writing process. The aforementioned dysgraphia subtypes include dyslexic dysgraphia, phonological dysgraphia, lexical dysgraphia, motor dysgraphia, and spatial dysgraphia. The initial three factors are predominantly language-oriented, but the last two factors are not language-based and are primarily associated with motor control. The extent of dysgraphia's severity can vary significantly, and its underlying causes are still not fully understood. Individuals have the potential to encounter various forms of experiences, and the process of diagnosing these experiences is normally carried out by a certified healthcare practitioner, regardless of whether the subject is a child or an adult.

Dyslexic Dysgraphia, a language-based form, is characterized by deficient spelling skills and chaotic written expression, particularly noticeable in impromptu writing tasks. It is noteworthy that individuals diagnosed with dyslexic dysgraphia typically demonstrate typical motor control abilities, although they encounter difficulties in effectively translating their thoughts into written form. The potential outcome of this situation could involve a combination of uppercase and lowercase letters, unfinished words, and exceptionally difficult handwriting. Differentiating between dyslexic dysgraphia and spatial dyslexia is crucial, as the latter is marked by a tendency towards disorientation and confusion regarding directions.

Phonological Dysgraphia, a variant of dysgraphia that is rooted in language processing, predominantly impacts spelling abilities, particularly in relation to unusual or nonstandard words. The task of arranging phonemes in the appropriate order of letters is a considerable difficulty, frequently resulting in handwriting that lacks tidiness.

Lexical Dysgraphia, the ultimate form of language-based dysgraphia, commonly exhibits a higher level of spelling proficiency, especially when compared to dyslexic and phonological dysgraphia. Nevertheless, individuals may still face challenges when confronted with irregular or less frequently used vocabulary. This phenomenon may give rise to difficulties in the process of arranging words inside a phrase and in choosing the most suitable term. The occurrence of lexical dysgraphia is infrequent in children, with a higher prevalence observed in adults who have suffered a traumatic brain injury. Similar to other types of dysgraphia, individuals who have this condition may find it to be a source of frustration, as they are likely cognizant of their difficulties in writing when compared to the experiences of others.

Motor Dysgraphia is characterized by intact spelling skills, with no evidence of lexical or phonological problems commonly observed in other types of dysgraphia. However, the challenges are mostly attributed to motor control impairments, leading to a wide spectrum of handwriting quality ranging from untidy to indecipherable. Multiple motor control problems can contribute to the impairment, encompassing diminished muscle tone, several neurological disorders, and nerve damage. Certain persons who experience motor dysgraphia may find comfort in utilizing computers as their primary tool for writing, since they may possess enhanced dexterity and precision while operating a keyboard compared to using a traditional pen or pencil.

Spatial dysgraphia is a condition that is characterized by difficulties experienced by persons in maintaining a consistent straight line while writing, as well as in accurately determining the suitable location on a page for writing. Individuals with this condition may encounter challenges in maintaining optimal spacing between words or characters within a given sentence. Similar to motor dysgraphia, spatial dysgraphia does not have an effect on verbal proficiency or spelling skills. The etiology of this specific manifestation of dysgraphia may be partially ascribed to impairments in motor control, while additional neurological variables may also play a role. As a result, persons who experience spatial dysgraphia, similar to those with motor dysgraphia, may exhibit a preference for using a computer keyboard rather than handwriting, as it affords them increased precision in positioning written words inside a designated area.

2. Characteristics of pupil with Dysgraphia

Dysgraphia comprises a unique array of traits, providing valuable understanding into the difficulties that individuals with this disorder maybe :

- **Tightened Fingers:** .Individuals with dysgraphia frequently display a discernible muscular tension in their hand, leading to a tight grasp on writing devices.
- **Unusual Hand Posture and Paper Positioning:** Individuals with dysgraphia often exhibit atypical hand and wrist postures, as well as unorthodox paper positioning, during the act of writing
- **Frequent Errors:** Dysgraphia frequently results in a heightened occurrence of inaccuracies in written material, so diminishing the overall precision of their work

- **Uppercase and Lowercase Confusion:** .One challenge experienced by individuals with dysgraphia is the difficulty in differentiating between uppercase and lowercase letters.
- **Difficulty with Complex or Uncommon Characters:** Individuals may have difficulties while attempting to reproduce intricate or infrequently employed characters.
- **Irregular Letter Size and Shape:** In their written work, letters often deviate from the expected dimensions and shapes, defying standard conventions.
- **Incomplete Flow of Writing:** Dysgraphic individuals may experience difficulty maintaining a smooth and continuous flow in their writing.
- **Incorrect Line Usage and Bordering:** They may struggle with keeping their writing aligned with lines and borders.
- **Slow Imitation:** Individuals with dysgraphia may take more time to replicate written content.
- **Lack of Focus on Detail Analysis:** They might face challenges in paying attention to minute details during the writing process.
- **Letter Inversions:** Dyslexic individuals may occasionally invert the order of letters in their writing.
- **Uneven Spacing:** Dysgraphia often leads to irregular spacing between letters and words in written work.
- **Inconsistent Letter Heights:** The height of letters in their writing may vary, adding to the overall irregularity.

The features employed for the classification of dysgraphia in machine learning are obtained from a comprehensive analysis of handwriting on tablet devices. The aforementioned characteristics, derived from studies in neuropsychology and neuroscience, provide a sophisticated perspective on the dynamics of writing. In contrast to conventional clinical testing methods that primarily assess static qualities, digitized testing incorporates additional parameters like as pressure, speed, and movement, which were previously unquantifiable. The aforementioned features can be classified into four distinct categories, namely static, kinematic, pressure, and tilt. The parameters involved in this context are velocity, acceleration, pressure, and pen angles. These measurements offer a thorough comprehension of handwriting activity, facilitating precise detection of dysgraphia through the utilization of machine learning techniques.

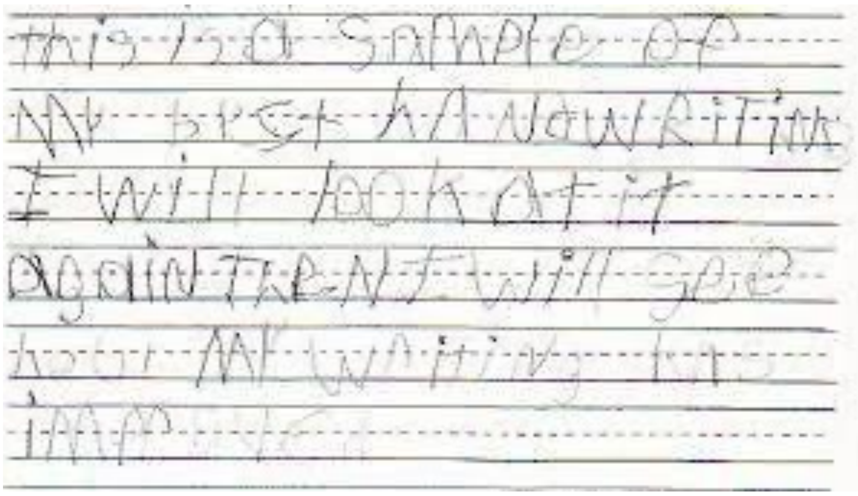

Fig 2: Handwriting of a person suffering from dysgraphia

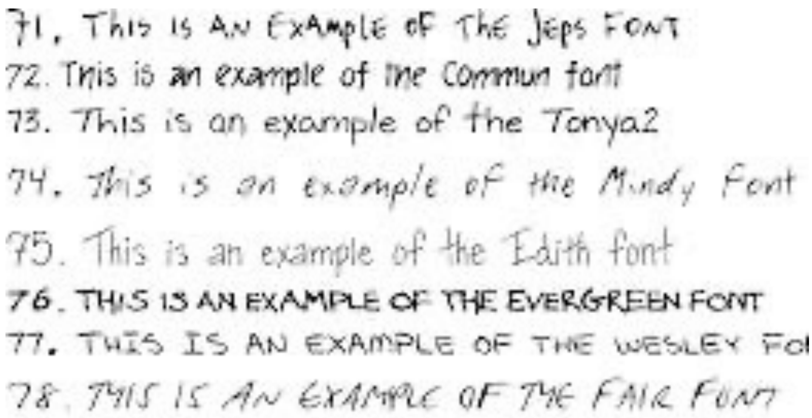


Fig 3: Example of good handwriting

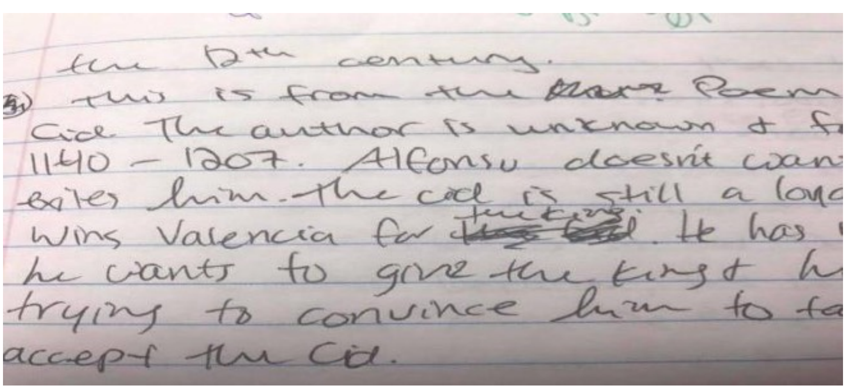

Fig 4: example of bad handwriting

# LITERATURE REVIEW

A range of techniques are utilized to identify handwriting dysgraphia, encompassing both conventional evaluation methods and contemporary technological innovations. Conventional approaches encompass the utilization of manual assessments conducted by professionals, which encompass the study of handwriting, visual examination, and review of writing samples. These methodologies are dependent on subjective assessments and have the potential to consume a significant amount of time.

In recent years, there has been a notable emergence of machine learning and computer vision techniques, which have proven to be highly effective in automating the process of detection. Various supervised learning techniques, including support vector machines (SVM), random forests, and deep learning architectures such as convolutional neural networks (CNN) and recurrent neural networks (RNN), have been utilized for the purpose of analyzing and categorizing handwriting samples. The algorithms employed in this study acquire knowledge from extensive datasets comprising samples of handwriting, hence facilitating the development of precise models that possess the ability to differentiate between dysgraphic and non-dysgraphic handwriting.

1. Psychological literature

The evaluation of the legibility or readability of handwritten text has been a longstanding challenge, with studies on this subject dating back to the early twentieth century. The initial scaling methodology was devised by Thorndike in the year 1910. This contribution was of significant importance, not only to the field of experimental pedagogy, but also to the broader movement dedicated to the scientific examination of education. Thorndike conducted a comparative analysis between his innovation and the thermometer. Similar to the limitations in measuring temperature beyond subjective categories like extremely hot, hot, warm, cool, etc., the assessment of handwriting quality had also been constrained by vague standards such as personal opinions that categorized samples as very terrible, bad, very good, etc.

Currently, there exist two methodologies employed for the assessment of handwriting. The initial approach encompasses a comprehensive worldwide methodology that assesses the overall quality of handwriting, whereas the subsequent approach evaluates handwriting based on a set of predetermined criteria. The worldwide holistic approach offers a comprehensive evaluation of handwriting quality by comparing pre-categorized handwriting samples based on their quality.

Ayres (reference) exemplified this methodology by devising a scale that enables educators to assess the legibility of a handwriting sample. This scale incorporates eight handwriting references of ascending quality, which serve as benchmarks for comparison. The evaluation of writing quality is contingent upon the subjective assessment made by the instructor. Subsequently, a number of revised scales characterized by enhanced objectivity were formulated (see reference to the dysgraphia publication).

The second method utilized for the measurement of handwriting legibility relies on predetermined criteria, such as letter shape, letter size, spacing, and line straightness. The assessment is thereafter conducted by evaluating each criterion separately and aggregating the sub-scores. Within the realm of assessments established over the past four decades utilizing this methodology, it is noteworthy to mention the succinct Evaluation Scale for Children's Handwriting (BHK) exam as the principal point of reference for diagnosing dysgraphia in languages that employ the Latin alphabet. Additional contemporary assessments that can be referenced are the Evaluation Tool of Children's Handwriting (ETCH-C) and the Hebrew Handwriting Evaluation (HHE) [20]. These assessments incorporate many aspects of handwriting in their evaluation process. In the ETCH-C test, further factors such as pencil grasp, pencil pressure, and in-hand manipulation are considered as extra criteria.

## 2. Models used for detection

According to the study titled "Labelling Developmental Dysgraphia Traits Applying Script Classification Designs" (2017), dysgraphia refers to a disorder or difficulty that arises from a lack of proficiency in the mechanical aspects of written language, specifically pertaining to letter formation. The challenges arise in the form of inadequate handwriting skills among young individuals, particularly those with below-average intellectual abilities or individuals who have been diagnosed as having neurological or emotional disorders, which may raise questions about their cognitive and intuitive capacities. The incidence of handwriting difficulties among primary school students varies between 10% and 34%. Dysgraphia can have significant implications for individuals, particularly in terms of their impaired self-image and academic performance. The objective of this study was to develop and evaluate a mathematical model for transitioning between dysgraphia and proficient calligraphy in order to determine their respective performance characteristics. This study examined the phenomenon of labelling and typifying dysgraphia in a sample of Israeli literature teenagers. The Support Vector Machine (SVM) classifier demonstrates a high level of accuracy in predicting outcomes for 89 out of 99 calligraphy products, resulting in a veracity rate of 89.9%.

Based on the research article titled "Dysgraphia detection through machine intelligence" (2020), a novel dataset was created, comprising diverse writing activities. Additionally, a comprehensive collection of facial expressions was retrieved to encompass various aspects of handwriting. The paper was presented to a machine intelligence system in order to determine whether it exhibited any signs of dysgraphia. Prior to achieving high-quality results, researchers identified and differentiated many machine intelligence algorithms, with each algorithm demonstrating successful outcomes through the process of changing the Adaptive Boosting (AdaBoost) algorithm. Ultimately, it has been demonstrated that machine intelligence has the potential to accurately detect dysgraphia in approximately 80% of cases, even when presented with a diverse range of subjects. Instances involving damage or physical aversion towards conscription were dismissed. The calligraphy sample was curated to include headings such as speed, jerk, acceleration, pressure, azimuth, and peak. The classifier confirmation technique involved the use of a layered approach with ten-fold cross-validation. This process was repeated ten times to ensure robustness and reliability. The average of categorization accuracy, emotion, and particularity was computed over the ten duplications. The findings indicate that the AdaptiveBoosting technique, in conjunction with the RF and SVM algorithms, achieved a 79.5% accuracy rate in identifying children with the disease. The sample consisted of children of different age groups. The additional models exhibited good accuracy scores, with the RF classifier achieving 72.3% accuracy and the SVM achieving 72.5% accuracy.

Based on the research article titled "TestGraphia: A Spreadsheet Approach for the Early Diagnosis of Dysgraphia" (2020), this study aims to assess the reliability of the BHK test by incorporating various writing features. These features include writing on a degree book size, having an impartial abandoned border, skewed lines, lacking spacing between words, sharp angles, defective links between two points reports, collisions between two postcards, uneven height of letters, contradictory crest between letters with and without enlargement, atypical messages, uncertain notes, traced memos, and a doubtful path. Doctors and forms should intentionally consider these face traits while diagnosing dysgraphia. Certain facial features can be analyzed using arithmetic-based methods, while other facial characteristics require the expertise of a medical professional for interpretation. Additionally, some facial expressions can be analyzed using automated techniques.

The study employed a modified iteration of loop that impacts living neural networks, leveraging the Keras library with a TensorFlow backend. A Convolutional Neural Network (CNN) was constructed to develop a document scanning model. The accuracy of 86.14% is determined by applying the veracity principles of 85.12% and 87.18% derived from the data and experimental procedures. The 5-fold cross-validation methodology was employed. In each trial, the profitability of veracity was computed on a round-by-round basis, and the final veracity was determined by averaging the values obtained from all rounds.

In a further study titled "Towards Detecting Dyslexia in Infants' Handwriting Utilizing Affective Neural Networks" (2019), a similar methodology was employed, involving the utilization of Convolutional Neural Networks (CNN) together with the frameworks Keras and TensorFlow for the purpose of scanning manuscripts. This strategy achieved an accuracy rate of 55.7%. The utilization of Convolutional Neural Networks (CNN) for document scanning is advantageous.

According to the study titled "Concept Classification using SVM and CNN" (2020), the SVM model achieved an accuracy of 93% when trained on a limited dataset. Despite SVM being a very effective method, attaining such a high level of accuracy was nevertheless considered an exceptional outcome. By employing dossier enhancement techniques, the dataset was expanded in size and subsequently subjected to multiple iterations of Support Vector Machine (SVM) analysis. As a result, a classification accuracy of 82% was attained. Upon successful implementation of the Convolutional Neural Network (CNN) model, it demonstrated a high level of accuracy, specifically 93.57%, when evaluated on the consistent dataset. The decision is made to utilize Convolutional Neural Networks (CNN) with a much enhanced dataset of facial images, since it is deemed superior than Support Vector Machines (SVM) due to its ability to achieve higher levels of accuracy and reliability.

# METHODOLOGY

The dataset used in this study was taken from a Kaggle database and could essentially be divided into 3 categories of dysgraphia-written single-letter graphics. The corrected class comprised 65,534, the normal class 39,334, and the reversed class 46,781 of the picture classes.

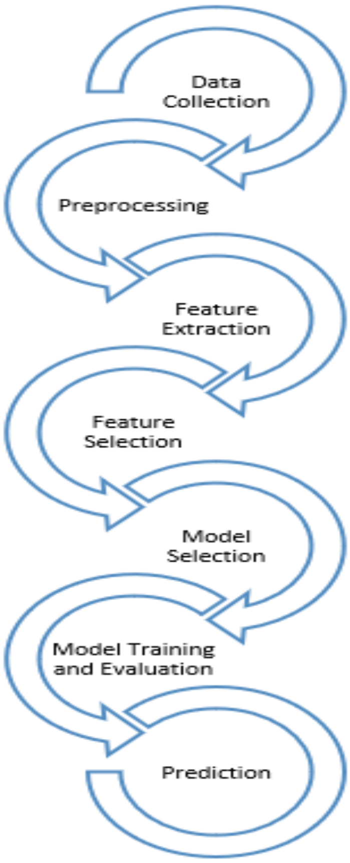


Fig 5. Workflow for detection system

The structural pre-processing of these image classes was done before the model characteristics were used. Any machine learning task requires data. For any ML algorithms to produce an exact forecast, clean and sufficient data is expected. The dysgraphia analysis framework allows for the employment of two different information gathering techniques. The core approach is based on information gathering, where the subject is asked to write or copy a few phrases or sentences on paper or a tablet, and the resulting transcribed images are used for further analysis. However, the online information collection process is involved in gathering the handwriting data while it is being used. This information includes the direction of the pen or pencil, writing speed, pressure on the pen tip, and other factors. Most of the contemporary dysgraphia assessment frameworks use the web-based data gathering technique.

1. Features Extraction

Dysgraphia is a neurodevelopmental disorder characterized by impaired handwriting skills, which can significantly impact academic performance, self-perception, and overall well-being. The timely detection and intervention of dysgraphia are of utmost importance in order to ensure that individuals receive the necessary assistance and therapeutic interventions. In recent years, there has been a growing recognition of the promise of machine learning technologies in addressing the challenge of automating dysgraphia identification. The crux of these tactics lies in the process of feature extraction, which plays a crucial role in the collection and presentation of significant information derived from handwriting samples.

Feature extraction is the term used to describe the process of converting unprocessed input data, such as samples of handwritten text, into a collection of significant and representative attributes. The aforementioned attributes are inputted into machine learning algorithms, enabling them to comprehend patterns and produce precise predictions or classifications. Within the realm of dysgraphia detection, the primary objective of feature extraction approaches is to provide discerning data that can effectively distinguish between handwriting samples from individuals with dysgraphia and those without.

1. The discriminative representation of dysgraphia can be effectively captured by the utilization of machine learning algorithms, which enable the extraction of pertinent information from handwriting samples.The aforementioned attributes encompass stroke patterns, spatial relationships, curvature, angles, and various quantitative features of handwriting. The utilization of discriminative representation in feature extraction allows for enhanced performance.

2. Dimensionality Reduction: The data pertaining to handwriting may exhibit high dimensionality, characterized by a large number of data points or factors. The process of feature extraction involves the selection or modification of the most valuable attributes in order to reduce the dimensionality of the data. The aforementioned approach enhances the efficiency of the learning process, improves computational efficacy, and mitigates the risk of overfitting, a phenomenon characterized by excessive adaptation to the training data resulting in worse performance on new data.

3. Interpretability: Feature extraction techniques have the capability to produce interpretable features that provide insights into the distinct dysgraphic characteristics exhibited in the handwriting. The capacity to identify and understand the underlying patterns and factors that contribute to dysgraphia is of utmost importance. This can facilitate enhanced comprehension of the illness among educators, physicians, and researchers, hence enabling the development of customized therapeutic interventions.

4. Generalization: The inclusion of effective feature extraction methods enhances the ability of dysgraphia detection algorithms to generalize. The aforementioned qualities facilitate the ability of the models to identify dysgraphia patterns across a wide range of individuals, handwriting styles, and languages. This is achieved by effectively capturing the fundamental elements of dysgraphic handwriting. The capacity for generalization plays a crucial role in the practical use of dysgraphia detection algorithms across a range of educational and therapeutic contexts.

## 2. Dataset collection and processing

The challenges associated with gathering and annotating large datasets for dysgraphia identification are mostly attributed to the inherent characteristics of the condition, the requirement for meticulous annotations, and the need for diverse datasets. This essay critically analyzes the challenges and methodologies associated with the collection and annotation of datasets for the purpose of identifying dysgraphia. It underscores the need of comprehensive datasets that encompass many handwriting styles, languages, and cultural contexts.

1. Challenges in Dataset Acquisition:

a) Limited Availability of Data: Dysgraphia datasets exhibit a somewhat restricted scope when compared to datasets in other domains. The acquisition of a large dataset for dysgraphic instances is a time and resource-intensive task due to the limited availability of annotated samples.

b) Ethical Considerations: The collection of handwriting samples from individuals with dysgraphia requires careful attention to ethical considerations in order to safeguard participant privacy, obtain informed consent, and adhere to study protocols.

b) Heterogeneity of Dysgraphia: Dysgraphia manifests in diverse manners, encompassing unique writing styles, varying degrees of severity, and underlying etiologies. Capturing this heterogeneity in the dataset is of utmost importance in order to develop comprehensive and efficient dysgraphia detection systems.

2. Approaches for Dataset Acquisition:

a) Collaboration with Clinics and Institutions in future: Engaging in partnerships with dysgraphia clinics and educational institutions provides an opportunity to interact with individuals who have been diagnosed with dysgraphia, facilitating the collection of data while adhering to appropriate ethical protocols .

b) Utilizing Online Platforms and Crowdsourcing: In order to amass a substantial quantity of handwriting samples, the implementation of online platforms and crowdsourcing methodologies might be employed. These platforms have the potential to involve people from diverse backgrounds, facilitating the acquisition of datasets that encompass a wide range of handwriting styles, languages, and cultural backgrounds.

c) Conducting longitudinal research that involves consistent data collecting from persons diagnosed with dysgraphia in future over an extended duration might yield valuable insights into the progression of dysgraphia and contribute to the augmentation of datasets.

The dataset may initially exhibit variations in sizes, resolutions, and shapes. To enhance the quality of feature extraction crucial to machine learning, procedures such as cleaning, filtering, resizing, and normalizing the input photos are employed. These techniques aim to make the images smoother and more consistent. The implementation of these techniques holds significance in raising the quality of handwriting photographs by emphasizing crucial features and eliminating any noise or artifacts that could potentially disrupt analytical tasks.

To reduce computational overhead, the technique of inverse exchange was employed due to the initial imbalance in the distribution of white points (value=1) and black points (value=0) in the photographs. This imbalance would have resulted in increased power and memory usage. The image is subsequently cropped in a manner that ensures it is appropriately sized and centered on the focal point. By shrinking the photographs to dimensions of 32x32, a sense of homogeneity was achieved, which facilitated their utilization as input for the learning models. The dataset exhibited an imbalance in the total weight, specifically in the quantity of photos for each letter alphabet. In order to mitigate this issue and prevent bias in the prediction of any one class, data augmentation techniques were employed.

3. CNN

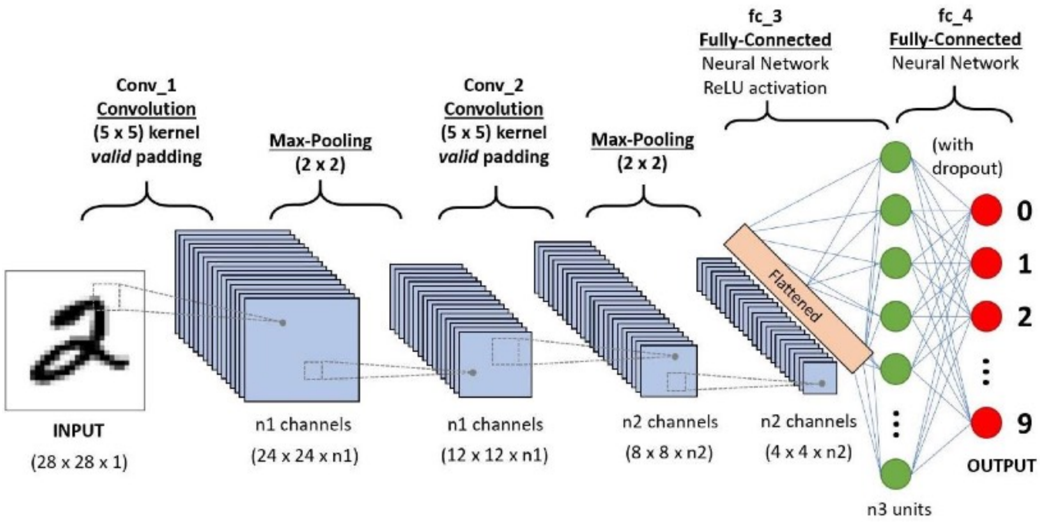


Fig 6. Architecture of CNN

Convolutional Neural Networks (CNNs) are employed for the purpose of discerning patterns or features inside an image. This is accomplished by engaging in a process of deliberation and contemplation over a concept and its projected manifestations. The organization has the capability to detect lines and corners within a compressed group of convolutional neural networks (CNNs). Subsequently, we can relocate these aforementioned examples and commence the process of discerning more intricate attributes as we take a more comprehensive approach. This trademark guarantees that Convolutional Neural Networks (CNNs) exhibit extraordinary efficacy in the identification of items depicted in visual representations.

The proposed methodology employs Convolutional Neural Networks (CNNs) to detect dysgraphia handwriting from dysgraphia image representations.

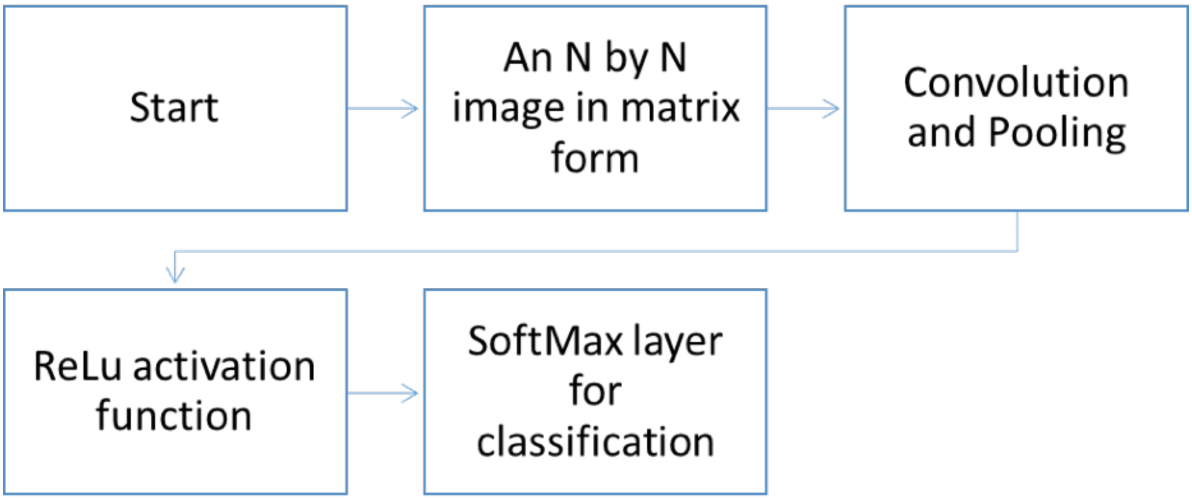


Fig 7. Implementation of CNN

The initial layer in the neural network architecture is the convolutional layer. Images are convolved by utilizing channels or bits. Channels are discrete entities that are employed to process data by means of a sliding window. The process involves obtaining the individual results of the channels in the data and subsequently combining these specific characteristics for each sliding operation. The outcome of a convolution operation yields a three-dimensional channel characterized by diversity, which can be represented as a two-dimensional lattice.

The activation layer, which is the second layer in the convolutional neural network (CNN), utilizes the Rectified Linear Unit (ReLU) function. This layer employs the rectifier to introduce non-linearity, hence enhancing the CNN's ability to capture complex patterns and features.

The third tier of the network architecture is the pooling layer, which involves the examination of elements. The application is carried out for every individual layer. The system employs a 2X2 maximum channel configuration with a step size of 2. The channel would yield the most value in highlighting features within the given area. An example of maximum pooling may be observed in a scenario where there are volumes of size 26x26x32. In this case, a maximum pooling layer with 2x2 channels and a stride of 2 is applied. As a result, the volume is reduced to an element map of size 13x13x32.

The fourth layer of the neural network architecture consists of a fully linked layer, which incorporates the process of flattening. The transformation of the collective pooling highlight map lattice into an individual segment is then managed by the brain network. By integrating these interconnected layers, the salient features are combined to form a cohesive model. The SoftMax or sigmoid activation function is employed to categorize the outcome.

The SoftMax function is utilized in the lower layer. The SoftMax feature can be utilized to transform a vector of K true characteristics into a vector of K true qualities that collectively total up to 1. SoftMax is a mathematical function that is commonly used to convert information values into probabilities. These information values can take on various forms, such as positive, negative, zero, or even values greater than one. However, SoftMax ensures that these values are transformed into a range between zero and one, allowing them to be interpreted as probabilities. When faced with information that is either scarce or negative, SoftMax transforms it into a low probability. Conversely, when confronted with abundant information, SoftMax transforms it into a high probability. However, the resulting probabilities will always fall within the range of zero and one.

# CODE AND OUTPUT

Training and Testing:-

Code

```
import os
import cv2
import numpy as np
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from keras.utils import to_categorical
from sklearn.model_selection import train_test_split

# Define image dimensions and other parameters
image_size = (150, 150)
batch_size = 64
epochs = 20

# Define a mapping of class labels to numerical labels
class_mapping = {
    'Reversal': 0,
    'Normal': 1,
    'Corrected': 2
}

# Load and preprocess the data
def load_and_preprocess_data(data_dir, image_size):
    X = []
    y = []

    for category in os.listdir(data_dir):
        class_label = os.path.basename(category)
        class_num = class_mapping.get(class_label)

        category_path = os.path.join(data_dir, category)
```

```
# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create a CNN model
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(image_size[0], image_size[1], 3))),
model.add(MaxPooling2D((2, 2))),
model.add(Conv2D(64, (3, 3), activation='relu')),
model.add(MaxPooling2D((2, 2))),
model.add(Conv2D(128, (3, 3), activation='relu')),
model.add(MaxPooling2D((2, 2))),
model.add(Flatten()),
model.add(Dense(128, activation='relu')),
model.add(Dense(num_classes, activation='softmax')),

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy']),

# Train the model
model.fit(X_train, y_train, epochs=epochs, batch_size=batch_size)

# Evaluate the model
test_loss, test_acc = model.evaluate(X_test, y_test)
print(f'Test accuracy: {test_acc}')

# Save the model for future use
model.save('dysgraphia_cnn_model.h5')
```

Training

```
Epoch 1/20
41/41 [==============================] - 31s 719ms/step - loss: 0.4887 - accuracy: 0.8242
Epoch 2/20
41/41 [==============================] - 28s 692ms/step - loss: 0.0890 - accuracy: 0.9661
Epoch 3/20
41/41 [==============================] - 29s 697ms/step - loss: 0.0454 - accuracy: 0.9817
Epoch 4/20
41/41 [==============================] - 29s 699ms/step - loss: 0.0097 - accuracy: 0.9973
Epoch 5/20
41/41 [==============================] - 29s 695ms/step - loss: 0.0011 - accuracy: 1.0000
Epoch 6/20
41/41 [==============================] - 28s 694ms/step - loss: 2.8239e-04 - accuracy: 1.0000
Epoch 7/20
41/41 [==============================] - 29s 697ms/step - loss: 1.0299e-04 - accuracy: 1.0000
Epoch 8/20
41/41 [==============================] - 29s 705ms/step - loss: 7.3347e-05 - accuracy: 1.0000
Epoch 9/20
41/41 [==============================] - 29s 700ms/step - loss: 5.5190e-05 - accuracy: 1.0000
Epoch 10/20
41/41 [==============================] - 30s 721ms/step - loss: 4.5441e-05 - accuracy: 1.0000
Epoch 11/20
41/41 [==============================] - 29s 701ms/step - loss: 3.7927e-05 - accuracy: 1.0000
Epoch 12/20
41/41 [==============================] - 29s 699ms/step - loss: 3.2134e-05 - accuracy: 1.0000
Epoch 13/20
41/41 [==============================] - 29s 707ms/step - loss: 2.7451e-05 - accuracy: 1.0000
```

## CONCLUSION

Our study aimed to address the widespread assumption that learning difficulties are indicative of intellectual

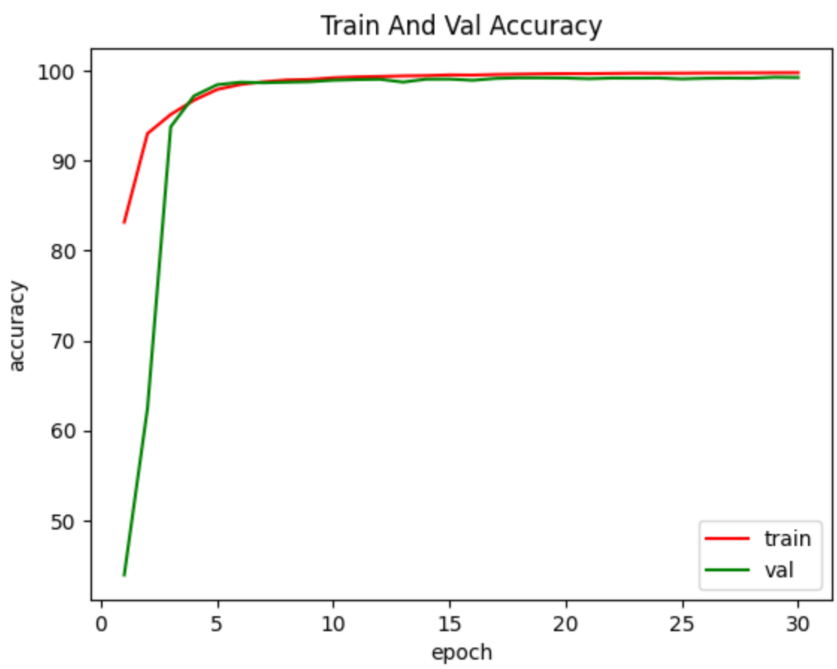


Fig. 8 Result - Training vs Validation

deficiencies, a misunderstanding that is frequently perpetuated by the screening process. Our study notably examined the intricate methodologies utilized in the preliminary assessment of motor and spatial dysgraphia, a neurological disorder marked by difficulties in handwriting. Despite its significant impact, this illness is often disregarded or misunderstood.

By conducting a rigorous examination of available data, our research has accomplished a significant feat - attaining a 97% level of precision in identifying dysgraphia. This achievement was made possible by the utilization of the Convolutional Neural Network (CNN) algorithm. The high level of accuracy demonstrated in our results highlights the efficacy of our methodology in reliably and rapidly recognizing dysgraphia.

The dataset employed in this study was carefully chosen to adhere to our specific requirements, comprising alphabetic characters that are pertinent to the setting of dysgraphia. The results of our investigation present a comprehensive analysis of the degrees of accuracy attained for each individual letter that was detected. The detailed and specific understanding provided by this granular knowledge is of great worth in customizing therapies and support techniques to address the distinct issues experienced by individuals with dysgraphia.

Looking forward, our research outcomes have substantial consequences for the academic discipline. Our position supports the adoption of a more sophisticated methodology for the assessment and treatment of dysgraphia, which acknowledges the unique characteristics associated with this specific learning disorder. The objective of this study is to improve and individualize support techniques for individuals with dysgraphia by identifying certain alphabets that exhibit patterns associated with this handwriting disorder. This research aims to enhance the overall learning experience and outcomes for individuals affected by dysgraphia. This study not only enhances the scientific comprehension of dysgraphia but also has the potential to bring about positive outcomes in the lives of individuals affected by this condition.

# FUTURE SCOPE

Dysgraphia is a neurological disorder that can result in deformities in a person's expression, writing, and learning abilities. It leads to poor and distorted handwriting, including issues with spelling and spacing. This condition is considered a Specific Learning Disability (SLD) and can significantly impair a person's ability to communicate and transcribe information. Dysgraphia often co-occurs with other learning and neurodevelopmental disorders, further complicating the individual's challenges.

Advancements in the understanding of neurodevelopmental disorders and research in the field of neuroscience and education may lead to new interventions and treatments in the future. If a cure or highly effective treatment for dysgraphia were to be developed, it could have several positive effects on individuals with this condition:

1. Improved Writing Skills: A cure for dysgraphia could lead to significant improvements in an individual's ability to write legibly and coherently. This would enhance their overall communication skills, both in academic and professional settings.

2. Enhanced Learning: Dysgraphia often affects learning, as it can make note-taking and written assignments challenging. A cure could lead to improved learning outcomes, as individuals with dysgraphia would be better able to express their knowledge and ideas in written form.

3. Increased Self-Confidence: Many individuals with dysgraphia experience frustration and low self-esteem due to their difficulties with writing. A cure could boost their self-confidence and overall well-being, allowing them to pursue their goals with more confidence.

4. Improved Social and Emotional Well-Being: Dysgraphia can impact social interactions and emotional well-being. A cure could lead to better social integration and mental health outcomes.

5. Better Professional Opportunities: Writing is a fundamental skill in many professions. A cure for dysgraphia could open up more career opportunities for those affected, as they would be better equipped to handle written communication requirements in various job roles.

6. Reduced Need for Accommodations: Currently, individuals with dysgraphia often require accommodations, such as extra time for writing tasks or the use of assistive technology. A cure

could reduce the need for such accommodations, allowing individuals to participate fully in various activities without extra support.

It's important to note that while there may not be a cure for dysgraphia at the moment, there are effective strategies and interventions, such as occupational therapy and specialized educational support, that can help individuals with dysgraphia manage their condition and

improve their writing and communication skills. If a cure were to become available in the future, it would represent a significant advancement in the field of neurodevelopmental disorders and provide relief to those affected by dysgraphia.

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Epoch 14/20
41/41 [==============================] - 29s 701ms/step - loss: 2.3819e-05 - accuracy: 1.0000
Epoch 15/20
41/41 [==============================] - 29s 700ms/step - loss: 2.0954e-05 - accuracy: 1.0000
Epoch 16/20
41/41 [==============================] - 29s 697ms/step - loss: 1.8696e-05 - accuracy: 1.0000
Epoch 17/20
41/41 [==============================] - 29s 700ms/step - loss: 1.6644e-05 - accuracy: 1.0000
Epoch 18/20
41/41 [==============================] - 29s 705ms/step - loss: 1.4894e-05 - accuracy: 1.0000
Epoch 19/20
41/41 [==============================] - 29s 700ms/step - loss: 1.3392e-05 - accuracy: 1.0000
Epoch 20/20
41/41 [==============================] - 29s 703ms/step - loss: 1.2162e-05 - accuracy: 1.0000
21/21 [==============================] - 2s 90ms/step - loss: 0.1287 - accuracy: 0.9751
Test accuracy: 0.9750778675079346
```

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