A Survey on Dysgraphia Detection Through Machine Learning/Deep Learning:

[Priyal Bansal, Paras Jain, Navyug Mohan, and Sanatan Shrivastava [Indian Institute of Information Technology, Kota, Rajasthan, India]

1. Introduction:

Dysgraphia is a combination of two Greek terms ‘dys’ means disability and ‘graphia’ means handwritten letter. Dysgraphia is a disease which causes writing disability. Dysgraphia mainly impacts handwriting skills, typing and spelling skills.
In the past, the term 'dysgraphia' has been used to refer to both motor coordination difficulties affecting writing, as well as persistent difficulty expressing thoughts in writing due to weaknesses in literacy and/or language conventions that includes grammar, spelling and punctuation. To avoid any confusion between the two, a distinction has more recently been made with a specific learning disorder in written expression (Dysgraphia) referring to:

(a) the language-based difficulties involved in constructing meaningful and effectively structured expressive writing and,

(b) It also points to the weakened capability in constructing meaningful, and precise structured effective writing. Persistent handwriting difficulties associated with an impairment in motor coordination are rather termed as Dyspraxia than Dysgraphia which is commonly understood to be a particular aspect of Developmental Coordination Disorder (previously known as Dyspraxia). Students with Dysgraphia have a severe problem of gathering the thoughts and writing it down physically. It is also observed often that students with Dysgraphia also have Dyslexia.

Handwriting at elementary school is an important mode to communicate, transmit, and record ideas and knowledge. It is a complex human activity that entails an intricate blend of cognitive, kinesthetic, perceptual motor components (Bonny, 1992) including visual perception, eye-hand coordination, visual-motor integration, kinesthetic perception, motor planning, dexterity and manual skills (Tseng & Cermak, 1993). The study of handwriting has importance beyond the issues of basic human perceptual-motor control. People with dysgraphia may speak more easily and fluently than they write, it is difficult to express while writing.

OBJECTIVE: The objective of this paper is to discuss the ongoing research and development towards detecting dysgraphia, by using the given handwriting of the person that is being tested on by using a set of Machine Learning/Deep Learning Algorithms and other generic python libraries. Another objective is to lay out a foundation on the types of Dysgraphia and their causes. Paper will also discuss the importance of detecting this disorder at an early stage or an early age of the child, and its effects on the overall growth and development (physically, psychologically, and physiologically) of an individual. Some qualitative methods of identifying the disorders are also discussed briefly in this paper. With the help of this paper, it is possible to understand how a person with dysgraphia is affected in a learning environment and in a workplace environment.

2. How dysgraphia affects a person and why is it to be diagnosed at an early age?

Students suffering from dysgraphia may also be accused of being sloppy/lazy because their handwriting isn't neat. This can affect self-esteem and lead to anxiety, a lack of confidence, and negative attitude toward education in general. In addition, Dysgraphia in a school setting can have enormous impact on the child's normal development as well as academic achievements.
Early diagnosis enables children to seek help and improve their writing sooner and helps teachers adapt their teaching style after properly diagnosing a source of learning difficulty in a child. Dysgraphia is not tied to Intelligence Quotient (IQ), so the students suffering from Dysgraphia can perform well if they receive the interventions and accommodations they need with proper assistance.
But most of the people are unaware of this issue and even if this came into the light, the process of detection might be very time consuming and hectic. The inefficiency of detection often wastes critical years of learning. The traditional methods for detection of Dysgraphia are discussed in further sections of this paper.

3. Types and Symptoms of Dysgraphia:

Dysgraphia is a common learning difficulty often recognized by poor writing abilities, can or cannot be determined through an academic progress report. Neurobiological and psychological disabilities contribute indirectly to the Dysgraphia symptoms prevailing in learner academic progress.

SYMPTOMS: Many experts view dysgraphia as an issue with a set of skills known as transcription. These skills include handwriting, typing, and spelling. Trouble expressing yourself in writing isn't part of dysgraphia. But when kids have to focus so much on transcription, it can get in the way of thinking about ideas and how to convey them.
One of the main signs of dysgraphia is messy handwriting.
These are some of the key handwriting skills kids may struggle with:

- ❑ Forming letters and spacing them correctly on the page.
- ❑ Writing the words/phrases/sentences in a straight line
- ❑ Writing the letters in the correct size
- ❑ Holding paper with one hand while writing on the other
- ❑ Holding and controlling a pencil/pen or any other writing
- ❑ Putting the right amount of pressure on the paper with a writing tool
- ❑ Maintaining the right arm position and posture for writing
- ❑ Trouble forming letters can make it hard to learn spelling.

That's why many kids with dysgraphia are poor spellers i,e. They have problems with spelling. They may also write very slowly, which can affect how well they can express themselves in writing and in general.It is important to set a mindset that having dysgraphia necessarily doesn't mean that a child isn't smart. And when kids with dysgraphia struggle with writing, they're not being lazy. But they do need extra help and support to improve.

CLASSIFICATION: Dysgraphia categorization is mainly under these subcategories:-

1) Dyslexic Dysgraphia
2) Motor Dysgraphia
3) Spatial Dysgraphia

Dyslexic Dysgraphia includes learners with illegible handwriting, spelling is poor but motor skills are fine. Dyslexic Dysgraphia presents combined symptoms of Dysgraphia caused due to dyslexia (not necessarily due to dyslexia).

Motor Dysgraphia presents a lack of fine motor skills, poor muscle strength, and neurobiological deficiency further presenting clumsiness and poor writing abilities. Gradual speed, illegible handwriting but correct spellings are the characteristics that determined Motor Dysgraphia.

Spatial Dysgraphia is a lack of knowledge of space that causes difficulty while writing and illegibility of written work, but speed and spellings are normal.

The types and their respective symptoms are summarised in the table given below.

S. No.	**Type**	**Symptoms**
1.	Dyslexic Dysgraphia	Moderate handwriting, poor spellings, Normal writing speed i.e, no problem with motor skills
2.	Motor Dysgraphia	Bad handwriting, correct spellings, slow writing due to muscle weakness and neurobiological deficiency
3.	Spatial Dysgraphia	Bad handwriting due to inconsistent spacing, correct spellings, Normal writing speed i.e, no problem with motor skills

4. Conventional diagnostic techniques:

The diagnosis of dysgraphia often involves several specialists, including a family doctor or pediatrician, an occupational therapist, and a psychologist. A doctor will need to rule out other conditions that could cause writing difficulties. Once they do this, a psychologist who specializes in learning disorders can diagnose dysgraphia. To do this, they may use:

- academic tests
- fine motor skill challenges
- IQ tests
- writing tests, such as writing sentences or copying words

During these tests, the specialist will observe the person’s pencil grip, hand and body position, and writing process. They will also examine the finished piece for signs of dysgraphia.The American Psychiatric Association’s Diagnostic and Statistical Manual of Mental Disorders (DSM-5) sets out criteria for diagnosing specific learning disorders, such as Dysgraphia.
Therapies: Occupational therapy (OT) is the main way to help kids who struggle with handwriting. Therapists can work with kids to improve fine motor skills and motor planning. Physical therapy can help with arm position and posture. These therapies may be available for free at school through an . Some parents may also pay for therapy outside of school.
Supports at school: Kids with dysgraphia may get help at school through an IEP or a . There are a number of accommodations for writing. Kids may also get assistive technology and other tools. These can range from simple pencil grips to dictation software. Help at home: There are lots of ways you can help your child with writing. Here are just a handful: Discover a drawing exercise for improving handwriting. See an expert explain how to use dictation software on a mobile device. Discover tools that can help with dysgraphia. Watch a video on how different pencil grips might help your child. Try multisensory techniques for teaching handwriting. Of

all the ways you can help, one is especially important. Showing your child that you're there to help and giving the right type of praise can build self-esteem and confidence. It can also help your child stay motivated to work on writing skills.

One of the criteria is that the set of symptoms should be present for at least 6 months, while appropriate interventions are in place.

There are various difficulties which are associated with conventional diagnostic techniques In French-speaking countries, the "BHK test" (The Concise Assessment Scale for Children's Handwriting) is widely used for diagnosing dysgraphia. This test is recognized by health insurance companies, which pay the costs of both diagnosis and treatment. But when it comes to diagnosing dysgraphia with the help of the BHK test, a number of difficulties may arise. These are related to the amount of time required for scoring the tests, variability across evaluators, and most notably the time lag – often a period of 6 months or more – between initial concerns about a child's handwriting and the opportunity to consult with an expert.

5. Dysgraphia prediction principle:

One of the main symptoms of dysgraphia is difficulty in writing. The idea is to gather writing text, from both dysgraphic and non dysgraphic writers, then to apply a machine learning algorithm. We expect the algorithm will learn the hidden characteristics allowing us to distinguish between those who have dysgraphia and those who are non-dysgraphic. Researchers have used many machine learning algorithms that can be used for the prediction(will be discussed in the section 6 of this paper).

The main issue that researchers were facing is to achieve decent accuracy as there is a shortage of data related to Dysgraphic children. As we all know that to train a machine learning algorithm, data is the most important part. The more data we have, the better will be the prediction.

6. Some ML Algorithms commonly used for dysgraphia prediction:

*6.1 **SVMs:***

Support vector machines (SVMs) are a set of supervised learning methods used for classification, regression and outliers detection. The advantages of SVMs are that they are effective in high dimensional spaces, they are also effective in cases where the number of dimensions is more than the number of samples, it also uses a subset of training points in the decision function i.e. it is also memory efficient. SVMs are very versatile i.e. custom kernels can also be specified for the decision function. The SVMs in scikit-learn support both dense and sparse sample vectors as input. However, to use an SVM to make predictions for sparse data, it must have been fit on such data.

Peter Drotár & Marek Dobeš[3] used SVM for detection of Dysgraphia and achieved an accuracy of $(78.8 \pm 2)\%$. Their study provides new data, a new orthography and an algorithm not previously used for dysgraphia recognition. They introduced several new features that have not previously been used to evaluate handwriting and dysgraphia. These features proved relevant for diagnosis and, moreover, offer a high level of interpretability. Rahul Budha Solanki, Sagar Praful Waghela & Radha Shankarmani[1] also used SVM for detection of Dysgraphia, though the exact accuracy has not been specified in their research paper. The SVM model is used to classify whether the child has any kind of writing disabilities or not, based on input features (slant of a letter, letter size, spacing, and pressure).

6.2 RANDOM FOREST:

A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. The sub-sample size is controlled with the max_samples parameter.

The advantages of random forest are:

- It is one of the most accurate learning algorithms available. ...
- It runs efficiently on large databases.
- It can handle thousands of input variables without variable deletion.
- It gives estimates of what variables are important in the classification.
  (3, 5 & 10)

Peter Drotár, Marek Dobeš have applied Random forest classifier and analyzed the handwritten content of 20 learners with Dysgraphia aged 4 to 14. Out of which 12 learners were males and 8 learners were females. 6 learners from the rural area and 14 were from the urban area, 4 learners have no experience of working on computers before and reported an accuracy of 79.50%.

6.3 ADABOOST:

AdaBoost technique follows a decision tree model with a depth equal to one. AdaBoost is nothing but the forest of stumps rather than trees. AdaBoost works by putting more weight on difficult to classify instances and less on those already handled well. AdaBoost algorithm is developed to solve both classification and regression problems.

Idea behind AdaBoost:

- Stumps (one node and two leaves) are not great in making accurate classification so it is nothing but a weak classifier/ weak learner. Combination of many weak classifiers makes a strong classifier and this is the principle behind the AdaBoost algorithm.
- Some stumps get more performance or classify better than others.
- Consecutive stump is made by taking the previous stumps mistakes into account.

6.4 NAIVE BAYES:

Naive Bayes classifiers are a collection of classification algorithms based on Bayes theorem and Naive assumptions. It is a family of algorithms where all of them share a common principle.

Naive assumptions are:

- No pair of features are dependent. For example, a person whose handwriting is slanted must not necessarily write using high pressure. Hence, the features are assumed to be independent.
- Secondly, each feature is given the same weight(or importance). For example, each feature of a person's handwriting will contribute equally in dysgraphia detection. None of the attributes is irrelevant and assumed to be contributing equally to the outcome.(5 & 8)

6.5 CONVOLUTIONAL NEURAL NETWORK:

- The convolutional neural network, or CNN for short, is a specialized type of neural network model designed for working with two-dimensional image data, although they can be used with one-dimensional and three-dimensional data.
- Central to the convolutional neural network is the convolutional layer that gives the network its name. This layer performs an operation called a "convolution".

- In the context of a convolutional neural network, a convolution is a linear operation that involves the multiplication of a set of weights with the input, much like a traditional neural network.(4)

6.6 K-MEANS CLUSTERING:

- **Clustering** is a technique widely used to find groups of observations (called clusters) that share similar characteristics. You don't have to specifically tell your algorithm how to group those observations since it does it on its own.
- **K-means** is probably one of the mostly known and frequently used. It uses an iterative refinement method to produce its final clustering based on the number of clusters defined by the user (represented by the variable *K*) and the dataset. For example, if you set K equal to 3 then your dataset will be grouped in 3 clusters and so on.(8)

6.7 LOGISTIC REGRESSION:

Logistic regression is a classification algorithm used to assign observations to a discrete set of classes. Some of the examples of classification problems are Email spam or not spam, Tumor malignant or benign and similarly **Dysgraphic or Non-Dysgraphic**.

Types of Logistic regression:

- Binary (Pass/Fail)
- Multi (Cats, Dogs, Sheep)
- Ordinal (Low, Medium, High)

As we can clearly see for our application we can use "Binary Logistic Regression".(5)

7. Handwriting analysis for diagnosis:

The important handwriting features used for disease diagnosis are:

1. **Congestion:** It is shown by letters having ovals and curls full of ink,
2. **Fragmentation:** It is shown by disconnected curves of letters,
3. **Direction of lines:** Horizontal Scaling, and Vertical Scaling
4. Layout of **Anomalies**
5. **Torsion:** It is an irregularity or luxuriating of part of a letter or entire letter,
6. **Shakiness**: It is small disruptions in strokes of letters,
7. **Slant:** It is an uneven inclined right movement of pen on paper while drawing letters,
8. Variation in **size** of letters while writing letters,
9. Alterations in **shape** of curves for similar letters,
10. **Breeze:** It is the part of stroke over sheet paper, when pen went without leaving ink,
11. **Pressure** applied on writing organ while writing (Hardware Oriented)
12. **Angle -** To find the angle

The Graphologists make use of a combination of two or more features mentioned above for handwriting analysis.

7.1 Offline Handwriting Analysis:

The traditional methods of handwriting analysis are based on text written on paper which is called as off-line handwriting. These methods include Clock Drawing Test (CDT) [6], Mini Mental State Examination (MMSE test) [7], House-Tree-Person (HTP) test [8]. In CDT, subjects have been asked to draw a clock with all digits pointing hands to 11:50. Alzheimer Patients face issues in placing digits; the clock digits may not evenly have been spaced or may show incorrect time. Scores are measured on a scale of 15 points, for shape and spatial arrangement of clock digits and hands. MMSE measures cognitive functions related to attention, language, registration, recall, calculation, orientation, and ability to follow simple commands. The test has 11 questions with a maximum score of 30-points. In HTP test patients have been asked to draw a tree, a house and a person. Along with drawing tasks, few questions are introduced to understand personality. The test may be extended to evaluate brain damage.

7.2 Online Handwriting Analysis:

With the evolution of the digital world, graphologists started using digital tablets which provided a richer set of measures on handwriting called online handwriting. The online analysis of handwriting finds temporal features such as inclination, time-stamp and pressure applied on pen, and velocity of the pen movements, which is not possible to capture in off-line handwriting [9]. However, on-line handwriting introduces distortion and transition trajectories (curves drawn for continuous or overlapped writing), which need to be removed before processing. Various classification and clustering techniques have been used to find out the best features suited for the analysis of targeted disease.

8. Data Collection:

Data is one of the most important components to make a machine learning model learn to predict. The data needs to be labelled, diverse and the bigger the dataset the better will be the model accuracy. But as Dysgraphia is not that common to be diagnosed and hence the data related to it is also limited.

Rahul Budha Solanki, Sagar Praful, Waghela Radha Shankarmani[1] collected data from a group consisting of children having Dysgraphia. They made them write a paragraph on paper and took photos of each paper from a mobile phone camera.

Sarthika Dutt, Neelu Jyothi Ahuja [2] have analyzed the handwritten content of 20 learners with Dysgraphia aged 4 to 14. Out of which 12 learners were males and 8 learners were females. 6 learners from the rural area and 14 were from the urban area, 4 learners have no experience of working on computers before. Children with emotional disorders and other disabilities have not been considered for the evaluation.

Peter Drotár & Marek Dobeš[3] collected data from 120 school children in the age group of 8 to 15 with 80 boys and 40 girls out of which 57 were diagnosed with dysgraphia and 63 were normally developing. Data from children with dysgraphia were collected by trained professionals at the Centre for Special-Needs Education in 2018 and 2019 as part of a standard assessment. Data from children without dysgraphia were collected by trained professionals at their elementary school. Data is available in public repository (https://github.com/ peet292929/Dysgraphia-detection-through-machine-learning) or upon requests from authors. Data was collected using a WACOM Intuos Pro Large tablet. The children wrote with a pen on paper that was positioned on the tablet. The tablet is capable of capturing five different signals: pen movement in the x-direction, pen movement in the y-direction, the pressure of the pen on the tablet surface, and the azimuth and altitude of the pen during handwriting.

Gilles Richard and Mathieu Serrurier[5] used a dataset composed of 1481 pictures of free handwritten text. Each text has at least five lines of text. Their dataset contains 198 pictures of peoples diagnosed with dysgraphia, about 13% of the dataset. For each picture of the dataset, the 9 features have been reported manually by a person. In order to avoid biases, this person was not aware of the diagnosis associated with the picture.

Sara ROSENBLUM, Ph.D , Shula PARUSH, Ph.D , Liora EPSTAIN, M.D. and Patrice L. WEISS, Ph.D [6] have used Two groups of handwriters (proficient and dysgraphic),each consisting of 50 third grade pupils, aged 8 and 9 years old, and 12 children with ADHD, aged 8 to 10 years were included in the study. Poor handwriters were identified via the standardized and validated Teachers' Questionnaire for Handwriting Proficiency

(Rosenblum, Jessel, Adi-Japha, Parush & Weiss, 1997) and the Hebrew Handwriting Evaluation (HHE) (Erez & Parush, 1999).

With the advancements in digital technology, graphologists are now using digital tools like tablet devices to capture 'online handwriting' which can capture a set of features of handwriting such as inclination of pen angle, pressure applied, velocity of the pen movements and various time stamps such as in air time, writing time and total time, which is not possible to capture in off-line handwriting. However, on-line handwriting introduces distortion and transition trajectories (curves drawn for continuous or overlapped writing), which need to be removed before processing. Various classification and clustering techniques have been used to find out the best features suited for the analysis of targeted disease.[8]

9. Implementation:

Will be merged with the Related Study Section .

11. Features Extraction:

Feature extraction is the first step in any problem which uses machine learning. In order to train the machine learning algorithm we need a set of labelled data.
Rahul Budha Solanki, Sagar Praful Waghela, Radha Shankarmani[1] used features including letter size, the slant of letters, spacing, and pressure from the image of a child. Given a text, all the characteristics and attributes such as Congestion, Fragmentation, Slant, Shakiness etc are being extracted out for the further processing that leads to detection of dysgraphia.
Sarthika dutt, Neelu Jyothi Ahuja[2] found that a handwriting evaluation framework based on Machine Learning and image processing (for feature extraction) is a better approach for handwriting analysis for Dysgraphia. It is capable of performing as a real-time framework for writing analysis.
To acquire the characteristics of handwriting Peter Drotár & Marek Dobeš [3] extracted several handwriting features that focused on the spatiotemporal and kinematic aspects of handwriting such as velocity, pressure, acceleration, jerk, azimuth, pen lift, etc. They ignored several more advanced features, such as non-linear features and spectral features as they found including these does not always help to increase the accuracy of the model and also increases the dimensionality of the data which lead to overfitting of the data, which negatively impacted the prediction performance of the classification algorithm. Gilles Richard and Mathieu Serrurier[5] used features including slant, pressure, amplitude, letter spacing, word spacing, slant regularity, size regularity and horizontal regularity. These features can be extracted using image processing or manually and given fairly high accuracy.
Some researchers used hardware based tools to collect real time handwriting features. Some have criticized this approach to collect handwriting data as students don't feel comfortable and might not be able to write naturally on screen like they write on paper.
Seema Kedar, D. S. Bormane, Sandeep Joshi[8] recorded data using a digital tablet device which captured various features such as spatial movements and pressure applied, pen tip movement.
Konrad Zo lna, Thibault Asselborn, Caroline Jolly, Laurence Casteran, Marie-Ange Nguyen-Morel, Wafa Johal and Pierre Dillenbourg[9] also collected data using tablet-based devices, according to them the main advantage of tablet-based systems is that it can capture the dynamic features of writing – something a human expert, such as a teacher, is unable to do. They showed that incorporating the dynamic information available by the use of tablets is highly beneficial to their digital test to discriminate between normal and dysgraphic children.

12. Related Study :

Rahul Budha Solanki , Sagar Praful Waghela ,Radha Shankarmani [1] discussed a model which can detect the presence of dysgraphia in a child and help parents to take necessary action on time. They have used the SVM ML algorithm for this.

Sarthika Dutt, Neelu Jyothi Ahuja [2] have used The handwriting evaluation framework that was based on a Pre-trained machine learning model (OCR) and image processing. It analyzes the handwritten documents and classifies the learner profile as a result..Study concluded that A handwriting evaluation framework based on Machine Learning and image processing is a better approach for handwriting analysis for Dysgraphia profiling. It is capable of performing a real time framework for writing analysis.

Peter Drotár, Marek Dobeš [3] have proposed a model that can be employed as part of a decision support system to assist professionals in occupational therapy to provide more objective diagnosis.
The proposed approach was able to recognize dysgraphic handwriting with almost 80% accuracy however, the dataset includes subjects aged 8–15 years.

Gilles Richard and Mathieu Serrurier [5] have used a Machine learning approach they have used a dataset Containing 1481 pictures of free handwritten text each of 5 lines. Out of which 13% were diagnosed with dysgraphia they have selected different feature such as Slant, Pressure, Amplitude, Letter Spacing, Word Spacing, Slant Regularity,Size Regularity, Horizontal Regularity and achieved an Accuracy of 90% using Random Forest.
Study Concluded that dysgraphia can be predicted with high accuracy from a simple analysis of a handwritten text.

Sara ROSENBLUM, Shula PARUSH , Liora EPSTAIN and Patrice L. WEISS [6] have used objective, digitizer-based data as an adjunct to conventional, subjective handwriting assessment in order to examine the contribution of each method to the identification and characterization of poor handwriting.
Research concluded that the subjective criteria used in this study (i.e., global legibility, letter erased or overwritten, unrecognizable letters, and spatial arrangement) have successfully discriminate between dysgraphic and proficient handwriting and the best discriminator amongst the objective measures was In air time.
the findings of this study serve to expand on the information provided by previous digitizer handwriting research and indicate that a correspondence exists between the subjective appearance of the written product of children with dysgraphia or ADHD and objective digitizer measures In air time and length).

Seema Kedar, D. S. Bormane, Sandeep Joshi[8] has reviewed research work carried out to diagnose diseases such as dysgraphia based on digital handwriting analysis. They used WACOM's INTUOS digitalizing tablet. To obtain Patient's handwriting It was found in the study that features related to motion, time and pressure are very helpful for diagnosis of health and mental diseases using digital handwriting analysis approach.

Konrad Zo lna , Thibault Asselborn , Caroline Jolly,Laurence Casteran , Marie-Ange Nguyen-Morel , Wafa Johal, and Pierre Dillenbourg [9] have showed that adding the dynamics of the movement improves the accuracy and decreases the necessary amount of information needed to deliver the identification of dysgraphic children

13. Summary of research related to Dysgraphia Detection:

S. No.	Author	Features Used	Algorithm Used	Accuracy	Dataset
[1]	Rahul Budha Solanki, Sagar Praful Waghela,	Slant angle, Pressure, Average letter size,	SVM	---	The group consisting of children having Dysgraphia disease is made to write a paragraph

	Radha Shankarmani	Thinking time, pen grip and Spacing			on paper.
[2]	Sarthika Dutt, Neelu Jyothi Ahuja	Handwriting, Spelling mistakes, writing speed	SSIM, Tesseract, Dictionary lookup	70%	20 learners with Dysgraphia and Table was also mentioned with repeated data.
[3]	Peter Drotár, Marek Dobeš	Velocity, acceleration, Pressure, Length of segment, Altitude, Pen Lifts, Width/Height of Segment, Duration	SVM, AdaBoost classifier, Random Forest	79.50%	https://github.com/peet292929/Dysgraphia-detection-through-machine-learning
[4]	Katie Spoon David Crandall Katie Siek	Demographics data along with handwriting	Convolutional Neural Network (CNN)	55.7±1.4%	We currently have 2 samples from students with dyslexia and 15 samples from students without dyslexia.
[5]	Gilles Richard and Mathieu Serrurier	Slant, Pressure, Amplitude, Letter Spacing, Word Spacing, Slant Regularity, Size Regularity, Horizontal Regularity	Random Forest, Naive Bayes, Logistic Regression	90%(Random Forest)	1481 pictures of free handwritten text each of 5 lines. Out of which 13% were diagnosed with dysgraphia
[6]	Sara ROSENBLUM, Shula PARUSH, Liora EPSTAIN and Patrice L. WEISS	Subjective measures: global legibility, letters erased and/or overwritten, unrecognizable letters and spatial arrangement Objective measures: total length, "on paper" length, in air length, total time, on paper time and in air time.	MANOVA	---	Digitizing WACOM Tablet and On-line Data Collection and Analysis Software
[7]	Kohli Maitrei and T.V. Prasad	Slower writing speed, characterized by irregularly formed letters, Use of inappropriate words when writing	Artificial Neural Networks (ANN)	75%	---
[8]	Seema Kedar, D. S. Bormane, Sandeep Joshi	Number of on-paper and in-air strokes while completing a task, Time, Width, height, orientation (slope) and length of segment.Spacing,pressure , Speed, Acceleration, Jerk, spectral density, deletions.	The ANOVA test, Naive Bayes, Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors, K-Means are most commonly used algorithms to model the data.	96%	INTUOS WACOM digitizing tablet using a wireless electron

[9]	Konrad Zo lna, Thibault Asselborn, Caroline Jolly, Laurence Casteran, Marie-Ange Nguyen-Morel, Wafa Johal and Pierre Dillenbourg	Letter form, letter size, spacing, and line straightness	Recurrent Neural Network model (RNN)	98%(Random Forest), 90%(SVM)	---
[10]	Thibault Asselborn1 , Thomas Gargot, Łukasz Kidziński, Wafa Johal, David Cohen, Caroline Jolly and Pierre Dillenbourg	Speed, pressure, tilt, space, density, size, tremor	Random Forest	96%	Data of 298 children, including 56 with dysgraphia. Children performed the BHK test on a digital tablet covered with a sheet of paper, then extracted 53 handwriting features.

14. CONCLUSIONS:

In this paper, we have analysed the research work related to the detection of Dysgraphia by various researchers around the world. Research work in this area has a wide scope due to its applicability for society. It is thus needed for faster and accurate detection of Dysgraphia. This paper includes both hardware and software detection methods. In hardware, there exists a tablet and a wireless pen which can collect data like pressure, duration, speed etc. that can be used for detection purposes.
Different types of ML algorithms can also be used(as specified under heading 6.) but as seen earlier there is a lack of classified data and it is a big obstacle which is very difficult to cross. Many researchers around the world are trying to gather classified data which can then be used to train the ML algorithm and predict the outcome (Dysgraphic / Non-dysgraphic) with good accuracy.We believe that this paper not only gives an insight into the type of research that has been done over the years, but also helps highlight the areas that need further experimentation and analysis. We wish to further our study in developing the ideal Dysgraphia detection system, which is accurate, efficient, and adequate, to make early detection and diagnosis of the handwriting disorders as quick and effortless as possible.

15. ACKNOWLEDGEMENT:

We thank Indian Institute of Information Technology, Kota for providing the support in terms of resources for the research work described in this paper.

16.REFERENCES :

[1] Dysgraphia disease detection using handwriting analysis Rahul Budha Solanki1 , Sagar Praful Waghela2 ,Radha Shankarmani 3 1,2,3 Information Technology, Sardar Patel Institute of Technology Mumbai, India (2020)

[2] A novel approach of Handwriting Analysis for Dysgraphia Type Diagnosis 1Sarthika dutt,2 Neelu Jyothi Ahuja 1Department of Systemics, University of Petroleum and Energy Studies. Dehradun, India (2020)

[3] Dysgraphia detection through machine learning Nature Research Peter Drotár 1 & Marek Dobeš (2020)

[4]Towards Detecting Dyslexia in Children's Handwriting Using Neural Networks Katie Spoon 1 David Crandall 1 Katie Siek 1 (2019)

[5] Dyslexia and Dysgraphia prediction: A new machine learning approach Gilles Richard 1 and Mathieu Serrurier 1 Dystech, Traralgon, Australia {gillesr,mathieus }@dystech.com.au (2020)

[6] Process Versus Product Evaluation of Poor Handwriting among Children with Developmental Dysgraphia and ADHD Sara Rosenblum (2000)

[7] Identifying Dyslexic Students by Using Artificial Neural Networks Ms Maitrei Kohli, Dr. T.V. Prasad, Member, IAENG proceedings of the World Congress on Engineering 2010 Vol I WCE 2010, June 30 - July 2, 2010, London, U.K

[8] Online Analysis of Handwriting for Disease Diagnosis: A Review 1* Seema Kedar, 2D. S. Bormane, 3 Sandeep Joshi (2018)

[9] The Dynamics of Handwriting Improves the Automated Diagnosis of Dysgraphia Konrad Zo lna ˙ 1,∗, † , Thibault Asselborn2,∗ , Caroline Jolly3,∗ , Laurence Casteran4 , Marie-Ange Nguyen-Morel4 , Wafa Johal2 , and Pierre Dillenbourg2 (2019)

[10] Automated human-level diagnosis of dysgraphia using a consumer tablet Thibault Asselborn1 , Thomas Gargot2,3,4, Łukasz Kidziński5 , Wafa Johal1,6, David Cohen2 , Caroline Jolly7,8 and Pierre Dillenbourg1 (2018)