Int. J. Nonlinear Anal. Appl. In Press, 3179–3188
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2022.25400.3005

# Identifications of developmental dysgraphia on the basis of dynamic handwriting features

Mohammad Amini[a], Alireza Tavakoli Targhi[b,*], Mehdi Hosseinzadeh[c,d], Faezeh Farivar[e], Reza Bidaki[f,g]

[a] *Department of Computer Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran*
[b] *Department of Computer Science, Shahid Beheshti University, Tehran, Iran*
[c] *Health Management and Economics Research Center, Iran University of Medical Sciences, Tehran, Iran*
[d] *Computer Science, University of Human Development, Sulaymaniyah, Iraq*
[e] *Department of Mechatronics Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran*
[f] *Research Center of Addiction and Behavioral Sciences, Shahid Sadoughi University of Medical Sciences, Yazd, Iran*
[g] *Diabetes Research Center, Shahid Sadoughi University of Medical Sciences, Yazd, Iran*

*(Communicated by Madjid Eshaghi Gordji)*

**Abstract**

Developmental disorders are regularly observed in developmental writing skills (developmental dysgraphia) with considerable concerns. Physicians do their diagnosis on the basis of the juvenile's written products as well as the attitudes and feedback taken from their teachers. This is a very laborious process and yet subjective in nature. Consequently, many juveniles suffering from this defect, particularly those with lower levels of the disorder remain undiagnosed. The aim of the present work was to find a new method for the automatic identification of dysgraphia even at minute levels. Utilizing the most sensitive pen tablet available to gather the desired dataset, we could extract all the considered datasets, i.e. temporal, spatial, kinematic, and pressure parameters with the greatest possible accuracy. On the whole, 102 students (both male and female) from the second, third, and fourth grades of primary schools were participated in the data collection phase by being asked to write a short paragraph. 51 students, in an age range of eight to ten years, were participated in each group, i.e. dysgraphic and non-dysgraphic. Next, a huge set of features (more than two thousand features) was extracted in the preprocessing phase. In the feature selection phase, we eventually ended up with sixteen features that proved to be the most effective in diagnosing dysgraphia. To distinguish between the dysgraphic and non-dysgraphic students, three different types of classifiers, i.e. random forests, AdaBoost classifiers, and support vector machines (SVM) were considered and compared. For the prediction of dysgraphia based on incessant handwriting features, the SVM was revealed to be the best model with a classification performance accuracy of 93.65%. Our work exhibited that online handwriting features including time, jerk, and altitude/azimuth may be utilized to automatically reveal dysgraphia in juveniles with this writing disorder.

Keywords: Diagnosis of Dysgraphia, Online Handwriting Features, Handwriting Analysis, Machine Learning, Classification
2020 MSC: 68Q32, 68T05

*Corresponding author
*Email addresses:* amini@iauyazd.ac.ir (Mohammad Amini), a_tavakoli@sbu.ac.ir (Alireza Tavakoli Targhi), hosseinzadeh.m@iums.ac.ir (Mehdi Hosseinzadeh), f.farivar@srbiau.ac.ir (Faezeh Farivar), rezabidaki@ssu.ac.ir (Reza Bidaki)

*Received:* November 2021 *Accepted:* April 2022

## 1 Introduction

Handwriting is regarded as an important skill essential for school children. Handwriting skills are a complex process that includes the cognitive, motor, and coordination skills as early as writing a book. Students need to integrate visual, motor, and conceptual skills into the writing process to master writing. The results of the related investigations have revealed that different handwriting features like timing or movement grading have been influenced if cognitive abilities and/or fine motor control are missing[14]. The relationship between hand-eye coordination and visual-motor integration with handwriting quality is believed to be dominant[23]. Hence, failure to integrate visual-motor dominating visual learning skills affects one's ability to form letters[7].

Students spend more than half of their time in class doing handwriting chores like dictating or copying[36]. 10-30% of these children are guessed to experience problems with handwriting during education, although most problems may not be sufficiently serious so that therapeutic measures are taken[14, 27]. Investigations have revealed that students with neat handwriting perform superior to their peers who have illegible handwriting. Failure to attain handwriting competence in primary school often hurts children's academic achievement and self-esteem[14]. Students that suffer from handwriting defects lose a significant time in planning, producing ideas, and rethinking their writings[37].

Juveniles with various kinds of developmental deficits typically have difficulty with handwriting. Developmental dysgraphia, i.e. developmental disabilities, in the development of writing skills is a common disorder with substantial outcomes. However, these disabilities have not been the focus of attention adequately. A significant proportion of children have developmental disruption. It has recently been evaluated that between 7 and 15% of school juveniles, in some form, suffer from development writing impairment[9].

The causes and effects of developmental writing defects are varied. In addition to impaired writing skills, typically, developmental dysgraphia results in more unfavorable effects. As far as a majority of dysgraphic juveniles are concerned, any writing task is a disaster. Trying to correctly pronounce words or write legibly is something extremely annoying for them[4, 18]. A child who needs to focus more on spelling words when writing a paragraph is probably less aware of the meaning of a paragraph than a child with normal spelling skills.

In recent years, innovative approaches to handwriting evaluation have been proposed using tablets with a stylus pen and machine learning techniques. In addition to achieving the handwriting process as written on paper, pen tablets can also record other data such as pressure, altitude, azimuth, timestamps, and pen data in the air. Using these online features, we will be able to analyze the handwriting process in greater depth and in a better manner. This technology, along with machine learning techniques, has been used to diagnose and find the relationships between disorders, diseases, and handwriting. In the examination of Parkinson's, online kinematic, pressure, and temporal features[12, 17, 31, 25, 1], visual attributes obtained from the pen tablet[29], and in-air movement characteristics have been used[13, 11]. Handwriting examination in children with ADHD (attention deficit hyperactivity disorder) has also resulted in significant consequences. Juveniles with ADHD had more inconsistent writing sizes in comparison with the control group[26]. Significant distinctions are observed in the writing speed measures amidst the two student groups students[6, 35, 32]. The benefits and impacts of using pen tablets in investigating the relationship between online handwriting features and developmental dysgraphia have been shown in previous researches. However, only a few studies using machine learning techniques have examined the auto-diagnosis of developmental dysgraphia.

In[28] a pen tablet was used to achieve handwriting and thus complex parameters were used to quantify the kinematics aspects and hidden complexities. An approach for the automatic diagnosis and description of dysgraphia in the juveniles of the third grade was explained in[33]. This approach was founded on the evaluation of the children's handwriting via registering the pen pressure on the paper and its position and direction utilizing a digital standard writing pad. Gargot et al.[16] Extracted twelve different digital characteristics of handwriting description from various aspects (i.e. static, kinetic, pressure and inclination) and utilized K-means clusters to diagnose dysgraphia. The result showed that machine learning with a wide range of online handwriting features such as pressure, altitude, and time could be effective in detecting dysgraphia[10, 8, 2].

At present, Dysgraphia is evaluated both manually and visually. This method is influenced by the mental state, visual abilities, tastes, and experience of the examiner and does not take into account features such as in-air features, timestamps, and pressure. The purpose of the present study is to establish a method for measuring handwriting with various factors such as kinematic, spatial, and temporal features, which -in addition to diagnosing dysgraphia- can be used in examining the association of other disorders with handwriting. It also provides an automated system for diagnosing developmental dysgraphia using online features.

Thus, the contributions of the present study are:

1. Collecting datasets from dysgraphic students. We got help from experienced teachers in data labeling, and it was also too late in the school year to get more confidence in data labeling.

2. Extraction of a huge set of handwriting features that are not related to a particular language. The proposed method of handwriting analysis can be used to diagnose diseases such as Parkinson and find the characteristics of handwriting in ADHD.
3. Providing an automated system for diagnosing dysgraphia even at low levels of the disorder. Our database contains borderline scores that increase the complexity of the diagnosis.
4. Extraction of several important features correlated with dysgraphia.
5. Creating an automatic diagnostic system in the Persian language
6. Providing a proposed method for handwriting analysis.

The remaining of this article is arranged in the following manner: Dataset, handwriting features, and classification are described in Section2. Section3 presents the results of the work. Section4 discusses and compares the results from the present work with those from recent studies and concludes with future work in Section5.

## 2 MATERIALS & METHODS

### 2.1 Subjects

On the whole, 102 cases (dysgraphic and non-dysgraphic) participated in this study, with each group consisting of 51 second, third, and fourth-grade male or female students. Their ages ranged from eight to ten years, and all of them were right-handed. For each group, 60% of the students were male and 40% of them were female. They were recruited from three public schools in Iran. All participants were born in Iran. The non-dysgraphic hand writers were matched to the participants in the poor handwriting group based on age, school, and grade. Samples were taken from three schools and 14 classes. The differences amidst the two mentioned groups concerning the ages and gender ratios were trivial.

All participants in the present work were recognized as cases with or without handwriting difficulties/ dysgraphia utilizing a standardized Questionnaire for Handwriting Proficiency Screening (HPSQ)[34]. The questionnaire was completed by the teachers. The questionnaire has been used in many articles (e.g.,[28, 33, 24]. In this questionnaire, scores above 14 are labeled as dysgraphia. Diagnosing this disorder based on the questionnaire is not an easy task because only a teacher who has worked with the student for a long time can do the labeling.

To ensure the accuracy of the data labeling, handwriting data collection, as well as questionnaires, were completed by the teacher when the school year was over so that the teacher had a deeper understanding of the student. We only used teachers with over 15 years of experience to be sure of the dataset labeling in the questionnaire section. Gathering such data from students of this age is a very difficult and time-consuming task. In addition to patience, it requires obtaining the necessary licenses and making the necessary coordination with parents, teachers, and school administrators.

### 2.2 Data Acquisition

A Wacom Intuos Pro Paper Large digitizing tablet equipped with a wireless pen with a tip sensitive to pressure was utilized for the data acquisition. This digitizer is the most sensitive pen tablet available, which can capture all kinematic, temporal, and pressure data with the highest possible accuracy when the electronic pen is on the surface (on-surface) as well as when it is located in the air (in-air). This system delivers precise spatial parameters when the electronic pen is hovered above the surface (up to approximately 10 mm from the tablet surface). The advantage of using in-air data is to record the movements of the student's wrist and hand, even when the pen is not on the screen, the movement and rotation of the wrist and hand can provide very valuable information.

Data collection software is not able to detect letters and words. It only analyzes strokes, that is, the curved lines from the very point at which the electronic pen contacts the surface to the point that it leaves it (on-surface strokes) and also, from the point the pen leaves the paper until the point the pen touches the paper (in-air strokes). For data collection purposes, we developed a custom tool.

Children were asked to write a short paragraph on a piece of paper (A4 size) attached to the tablet surface. The tablet was placed on a table at a position comfortable for writing. A few examples of the signals are shown in Figure 1.

Figure 1(a) shows a handwriting sample from a non-dysgraphic subject with HPSQ=2 while Figure 1(b) illustrates a sample from a dysgraphic subject with HPSQ=16. The reader can notice in Figure 2, the handwriting of the

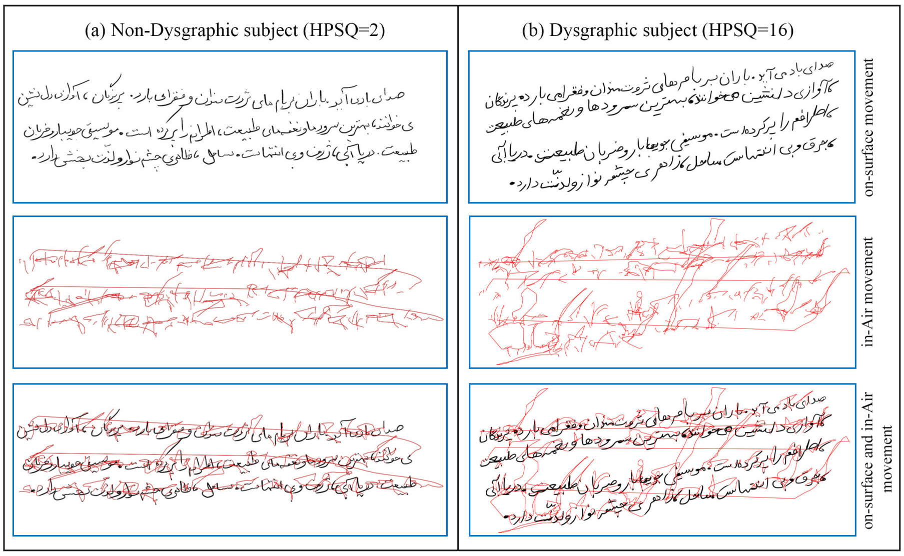


Figure 1: an example illustrating on-surface (black) and in-air (red) lines and both movements when writing a paragraph by children without (Controls) and with dysgraphia (Dysgraphic) from our database

dysgraphic subject has more regularity in both the text on the surface and the pen movement in the air. A number of other handwritten samples are given in Appendix.

An instance of a child's handwriting, including the first sentence of the paragraph and all signals taken by the tablet is illustrated in Figure 2.

### 2.3 Handwriting Features

In the first stage of feature calculation, kinematic features including length, width, velocity, speed, acceleration, orientation, and jerk were extracted.

Next, we used post-processing on kinematic features such as the number of velocity changes (NCV), the number of changes in acceleration (NCA), relative NCV/NCA, relative NCV/NCA. As a set of temporal parameters, the time spent in-air namely the in-air duration, on-surface duration as well as in-air to on-surface ratio were analyzed.

Finally, it was necessary to transform vector representations into scalar values so that the conduction of the next processing was possible. For example, velocity was a vector feature. We used some kind of statistical functions including: Means, Maximum, minimum, Skewness, kurtosis, Moments, Median, Percentiles, Quartiles, Deciles, Range, Interquartile range, Standard deviation and Variance.

### 2.4 Feature Selection

Choosing the appropriate feature is among the crucial concepts in machine learning, which extensively influences the model performance as well as the process in which features with the highest estimation power are selected. In the previous step, a huge amount of features (around 2100 features) were obtained which is a problem known as the "curse of dimensionality" first introduced by Bellman[3]. Thus, keeping all features not only hugely increases the learning time but also diminishes the classification reliability and accuracy. Therefore, proceeding by approaches of dimension reduction is obviously inevitable and essential. We used the filter-based feature selection method because of the large quantity of the features and the reduced complexity of subsequent calculations.

As a pre-processing step, all the data was analyzed utilizing the Mann-Whitney U test to compare the groups (i.e. dysgraphic vs. non-dysgraphic). The significance level was chosen at $p < 0.05$. Those features incapable of passing the Mann-Whitney test were disposed of and were not included in additional processing. Irrelevant features can negatively affect the model performance. Redundant features do not add any information to the other features because they are correlated with each other or because they can be obtained by combining other features. Reducing data redundancy means increasing the accuracy, making no noise-based decisions, reducing complexity, and making the training faster. For this purpose, features with a correlation value above 0.8 were removed from the dataset.

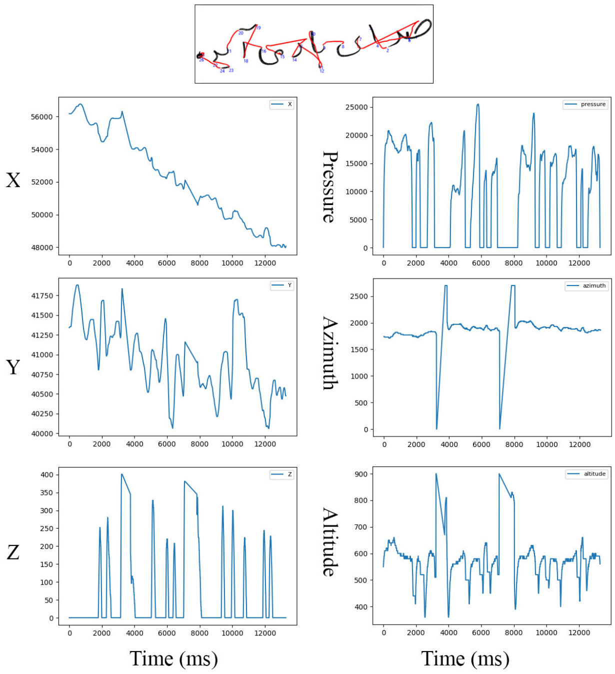


Figure 2: A child's handwriting sample including the first sentence of the paragraph and all signals are taken by the tablet.

Table 1: The ten features which had strong correlations with the target feature

| Feature | Pearson | Spearman | U Mann Whitney P-Value |
|---|---|---|---|
| Relative in-air time | 0.50405 | 0.49380 | 3.54E-07 |
| VNCV (in-air) | 0.48580 | 0.49946 | 2.63E-07 |
| Curve length (in-air) | 0.45049 | 0.46050 | 1.88E-06 |
| Orientation (in-air, harmonic mean) | 0.40174 | 0.39124 | 4.27E-05 |
| Vertical distance (in-air, skewness) | 0.39357 | 0.50112 | 2.42E-07 |
| Horizontal jerk (on-surface, standard deviation) | 0.38638 | 0.35861 | 1.59E-04 |
| Vertical jerk (on-surface, Geometric mean) | 0.35154 | 0.36460 | 1.26E-04 |
| Vertical jerk (on-surface, harmonic mean) | 0.34602 | 0.36194 | 1.39E-04 |
| Horizontal jerk (on-surface, max) | 0.34566 | 0.37926 | 7.00E-05 |
| Vertical acceleration (on-surface, percentile99) | 0.34408 | 0.34695 | 2.47E-04 |

Due to the overlap of many features, we obtained the most important features based on the Mann-Whitney test, Pearson and Spearman correlations and extracted unique features. Table 1 shows the ten features which had strong correlations with the target feature.

In the end, we select the best subset of features by choosing the classifier and wrapper-based features. Recursive Feature Elimination (RFE)[19] was used to select the best subset of features. The 16 features selected by RFE with the SVM estimator are shown in Table 2.

### 2.5 Classification

Our goal was to create a discriminatory model for the distinction between dysgraphic and non-dysgraphic students. This is indeed a binary classification problem, which may be solved using machine learning algorithms. Three methods of machine learning were compared, i.e. SVM, Random Forest, and AdaBoost. We used the Python programming language and the scikit-learn as a library[30].

The SVM model reduces the classification error to the lowest possible level while making the margin as great as it can to locate a separating hyperplane. As a result, different classes of data are identified. For a two-class support vector machine, one can think of the following decision function[11]:

$$f(x) = sgn[w^T g(x) + b] \tag{2.1}$$

Table 2: Best features selected by RFE

| in-air features | on-surface features |
|---|---|
| Relative time | Vertical jerk (harmonic mean) |
| Vertical distance (skewness) | Vertical acceleration (percentile99) |
| Vertical displacement (range) | Horizontal jerk (geometric mean) |
| Acceleration (Trim mean (50)) | Speed of altitude change (skewness) |
| Horizontal displacement (max) | Horizontal jerk (standard deviation) |
| Orientation (percentile40) | |
| Altitude (relative position of min) | |
| Azimuth (interquartile range) | |
| VNCV | |
| Orientation (harmonic mean) | |
| Speed of altitude change (kurtosis) | |

In the above equation, $w$ denotes the d-dimensional weight vector, while $b$ represents a bias. In order to find $b$ and $w$, an optimization problem with the following linear equality constraints is to be solved:

$$\min_{w,b,c_i} J = \frac{1}{2}w^T w + \frac{\gamma}{2}\sum_{i=1}^{N} c_i^2 \tag{2.2}$$

$$y_i[w^T g(x_i) + b] = 1 - c_i, i = 1, 2, 3, \ldots, N. \tag{2.3}$$

$N$ represents the number of the samples existing in the training data, $y_i$ denotes the target value of the training data, $\gamma$ is a hyperparameter used for regularization, and finally $c_i$ is the slack variable. By solving the Lagrangian (Lagrange functional), we have:

$$\phi(w, b, \alpha_i, c_i) = \frac{1}{2}w^T w + \frac{\gamma}{2}\sum_{i=1}^{N} c_i^2 - \sum_{i=1}^{N} \alpha_i\{y_i[w^T g(x_x) + b] + c_i - 1\} \tag{2.4}$$

The discriminant function for the separating hyperplane would be derived as

$$f(x) = sgn[\sum_{i=1}^{N} \alpha_i y_i K(x, x_i) + b] \tag{2.5}$$

in which $\alpha_i \in R$ is a Lagrangian multiplier while $K(x, x_i)$ represents a kernel function. To train nonlinear separated functions, the data is mapped in an implicit manner using a kernel function, in which a splitting hyperplane is located in a higher-dimensional space. The new specimens will be categorized based on their hyperplane side. We used a kernel of radial basis functions (RBF)[20]. The RBF kernel is defined as

$$K(x, x_i) = e^{\frac{-\|x-x_i\|^2}{2\gamma^2}} \tag{2.6}$$

in which gamma determines the RBF function width. Utilizing a grid search for some values, the gamma kernel parameters and the penalty parameter were optimized. We did our search over a grid, which was defined by multiplication of two sets, i.e. $C = [2^{-8}, 2^{-7}, ..., 2^7, 2^8]$, $Gamma = [2^{-12}, 2^{-11}, ..., 2^{11}, 2^{12}]$.

Random forest[22], as its name implies, contains a plethora of individual decision trees operating as an ensemble. In the random forest, each tree splits out a class prediction. Then the class becomes the prediction of our model with the most votes. A huge number of models (trees), which are relatively uncorrelated and serve as a committee, are better than the individual separate constituent models. The maximum depth of the tree was chosen to be 6 and the quantity of the trees existing in the forest was chosen to be 60.

Boosting is a very successful technique for the solving two-class classification problems[21]. In this work, we used the AdaBoost classification. It was first introduced by[15]. AdaBoost is among the most prominent methods of a group recognized as boosting. The basic concept behind the boosting approach is to utilize ensemble methods in order to conglomerate weak classifiers so that a robust learner is created. An iterative boosting algorithm, AdaBoost generates a robust classifier via a linear combination of frail classifiers. We used the decision tree classifier as a weak classifier[38]. The maximum quantity of estimators for which the boosting process came to an end was chosen to be 159. The learning rate that shrank each classifier's contribution was chosen to be 0.3.

Table 3: various types of classifiers compared for discrimination between Dysgraphic and non-Dysgraphic students from handwriting.

| Classifier | Accuracy | Sensitivity | Precision | Specificity | F1-Score |
|---|---|---|---|---|---|
| SVM | 0.936508 | 0.9368422 | 0.936842 | 0.9361703 | 0.936842 |
| AdaBoost | 0.915344 | 0.9263158 | 0.907216 | 0.9042553 | 0.916667 |
| Random Forest | 0.89418 | 0.9052632 | 0.886598 | 0.8829787 | 0.895833 |

### 2.6 Validation

For model validation cross-validation method was used. In machine learning, the main purpose of cross-validation is to assess the skill that a model of machine learning exhibits for an unseen new set of data. This means using a finite estimate of the sample in order to evaluate the performance of the model when using data projections not used during training. Validation of the classifiers was performed employing a cross validation technique called leave-one-out, which is indeed a logical limit case of the K-fold cross validation. In that case, K equals N that is the number of data points present in the dataset. In other words, the training of the function approximator is repeated for N times on all the data points in the data but for one. Subsequently, for that one single point, a forecast is made.

## 3 Results

The performance assessment of the trained classifiers was achieved by calculation of the accuracy, precision, sensitivity/recall, specificity as well as the F1-score on a test set of samples defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.1}$$

$$Sensivity/Recall = \frac{TP}{TP + FN} \tag{3.2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3.3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{3.4}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{3.5}$$

In the above equations, TP and FP indicate the number of dysgraphic individuals accurately diagnosed (true positive) and the number of students inaccurately known as dysgraphic (false positive). As well, TN indicates the number of students correctly diagnosed as non-dysgraphic (true negative) while FN indicates the number of students incorrectly diagnosed as non-dysgraphic (false negative).

The classification metrics for AdaBoost, SVM, and random forest classifiers are given in Table 3. A comparison of all three classifications reveals that the most promising results are obtained in all of the metrics using the SVM classification. Table 3 describes the Pearson and Spearman correlations of each feature with the target. As shown in Table 1, the five top features of great correlations with the target were in-air features, indicating that in-air features play a decisive role in identifying dysgraphia. The most important feature from the Pearson perspective was an in-air feature i.e. relative time which was a temporal feature. Also in previous studies, time has been recognized as an important feature in this area. Among the top ten features, jerk was of a particular significance, and four more features i.e. on-surface: horizontal jerk (standard deviation, max) and vertical jerk (geometric mean, harmonic mean) were related to jerk. The RFE selected 16 features based on time, jerk, altitude, acceleration, azimuth, distance, and orientation, of which eleven were in-air and five were on-surface, as shown in Table 2.

## 4 Discussion

For writing a single sentence a wide variety of strokes are involved, which are set at a precise speed and acceleration and require a great extent of synchronous processing. Consequently, they may impose a programming burden heavier than what is necessary for an ordered array of the same strokes [5]. We asked 102 students to write a short paragraph on a digitizer and a huge collection of features were extracted. Online handwriting features are of great importance in describing children's writings (e.g., [26, 28, 33]. Machine learning techniques and dynamic handwriting features have been used to diagnose dysgraphia, Parkinson's disease, and the relations amidst the attention deficit hyperactivity disorder and dynamic handwriting features (e.g., [17, 11, 35, 32, 28, 33]). We diagnosed dysgraphia using three classifiers; our best results were achieved by the accuracy of 93.6% in the SVM with the RBF kernel.

Our fascinating findings were the high impact of the time feature, in-air features as well as the high impact of the jerk feature. Contrary to our notion, although we used a very high-pressure sensing digitizer, the pressure feature did not play an important role in our work. Effective features found in the RFE output were in-air features i.e. azimuth (interquartile range) and altitude (relative position of min) indicating that one of the causes of dysgraphia was the misalignment of the pen in children with dysgraphia. This defect was corrected by training. The effective in-air features i.e. vertical distance (skewness) and vertical displacement (range) indicated that children with dysgraphia could not hold the pen in a fixed position.

We used the HPSQ to identify dysgraphic groups, which were based on teacher scoring; factors such as the experience and taste of the teacher can also affect the test, which might be due to the degree of classification error expected. Reducing bias in diagnosis is realized by increasing the number of children in the database and developing an automated diagnosis system.

By extracting more features, using more statistical features, examination of other categorization methods, and enriching the data, it seems possible to achieve more accurate automatic diagnosis of dysgraphia. Since the method we used did not depend on the specifications of the Persian language, it can be used for dysgraphia analyses in many other languages as well.

The most distinctive features we found were the two features VNCV (in-Air) and Relative in-Air Time. Considering that in VNCV (in-Air) feature, higher values were obtained for children with dysgraphia, it appears that children with dysgraphia have less control and stability than non-dysgraphic children. This seems to indicate that dysgraphic children have more time to make decisions about writing words.

## 5 Future work

In addition to the short paragraphs, the students were assigned ten more tasks consisting of drawing different shapes, sentences, and a number of consecutive letters. We will discuss them in other articles, which will be available in the future and since the method used is not unique to the specific language, it can be used in other languages. Using traditional machine learning techniques, we have been able to achieve a high accuracy in diagnosing dysgraphia and to train the system with the experience of several teachers with over 15 years presenting an artificial intelligence diagnostic system as an assistant psychiatrist and teacher. In-depth learning methods were studied but due to the small learning data, no acceptable results were obtained. Future work can be done by increasing data samples and using deep learning techniques, e.g. working on time series with LSTM or converting time series into images and using the CNN method to detect and rate this disorder.

## References


[1] A. Ammour, I. Aouraghe, G. Khaissidi, M. Mrabti, G. Aboulem, and F. Belahsen, *Online Arabic and French handwriting of Parkinson's disease: The impact of segmentation techniques on the classification results*, Biomed. Signal Process. Control **66** (2021), 102429.

[2] T. Asselborn, T. Gargot, Ł. Kidziński, W. Johal, D. Cohen, C. Jolly, and P. Dillenbourg, *Automated human-level diagnosis of dysgraphia using a consumer tablet*, NPJ Digital Medicine **1** (2018), no. 1, 1–9.

[3] R.E. Bellman, *Adaptive control processes: A guided tour*, Princeton university press, 2015.

[4] V.W. Berninger, *Coordinating transcription and text generation in working memory during composing: Automatic and constructive processes*, Learn. Disabil. Quart. **22** (1999), no. 2, 99–112.

[5] M.P. Broderick, A.W.A. Van Gemmert, H.A. Shill, and G.E. Stelmach, *Hypometria and bradykinesia during drawing movements in individuals with parkinson's disease*, Exper. Brain Res. **197** (2009), no. 3, 223–233.

[6] M. Brossard-Racine, A. Majnemer, M. Shevell, L. Snider, and S.A. Bélanger, *Handwriting capacity in children newly diagnosed with attention deficit hyperactivity disorder*, Res. Deve. Disabil. **32** (2011), no. 6, 2927–2934.

[7] C.J. Daly, G.T. Kelley, and A. Krauss, *Relationship between visual-motor integration and handwriting skills of children in kindergarten: A modified replication study*, Amer. Occup. Therapy **57** (2003), no. 4, 459–462.

[8] L. Deschamps, C. Gaffet, S. Aloui, J. Boutet, V. Brault, and E. Labyt, *Methodological issues in the creation of a diagnosis tool for dysgraphia*, NPJ Digital Medicine **2** (2019), no. 1, 1–3.

[9] S. Döhla, D.and Heim, *Developmental dyslexia and dysgraphia: What can we learn from the one about the other?*, Front. Psych. **6** (2016), 2045.

[10] P. Drotár and M. Dobeš, *Dysgraphia detection through machine learning*, Sci. Rep. **10** (2020), no. 1, 1–11.

[11] P. Drotár, J. Mekyska, I. Rektorová, L. Masarová, Z. Smékal, and M. Faundez-Zanuy, *Analysis of in-air movement in handwriting: A novel marker for parkinson's disease*, Comput. Meth. Programs Biomed. **117** (2014), no. 3, 405–411.

[12] ______, *Decision support framework for parkinson's disease based on novel handwriting markers*, IEEE Trans. Neural Syst. Rehabil. Engin. **23** (2014), no. 3, 508–516.

[13] P.r Drotár, J. Mekyska, I. Rektorová, L. Masarová, Z. Smékal, and M. Faundez-Zanuy, *A new modality for quantitative evaluation of Parkinson's disease: In-air movement*, 13th IEEE Int. Conf. Bioinf. Bioengin., IEEE, 2013, pp. 1–4.

[14] K.P. Feder and A. Majnemer, *Handwriting development, competency, and intervention*, Dev. Medicine Child Neuro. **49** (2007), no. 4, 312–317.

[15] Y. Freund and R.E. Schapire, *A decision-theoretic generalization of on-line learning and an application to boosting*, J. Comput. Syst. Sci. **55** (1997), no. 1, 119–139.

[16] T. Gargot, T. Asselborn, H. Pellerin, I. Zammouri, S. M. Anzalone, L. Casteran, W. Johal, P. Dillenbourg, D. Cohen, and C. Jolly, *Acquisition of handwriting in children with and without dysgraphia: A computational approach*, PLoS One **15** (2020), no. 9, e0237575.

[17] R. Graça, R. Sarmento e Castro, and J. Cevada, *Parkdetect: Early diagnosing Parkinson's disease*, IEEE Int. Symp. Medical Measur. Appl. (MeMeA), IEEE, 2014, pp. 1–6.

[18] S. Graham, V.W. Berninger, R.D. Abbott, S.P. Abbott, and D. Whitaker, *Role of mechanics in composing of elementary school students: A new methodological approach*, J. Educ. Psych. **89** (1997), no. 1, 170.

[19] I. Guyon, J. Weston, S. Barnhill, and V. Vapnik, *Gene selection for cancer classification using support vector machines*, Machine learning **46** (2002), no. 1, 389–422.

[20] S. Han, C. Qubo, and H. Meng, *Parameter selection in svm with rbf kernel function*, World Autom. Cong., IEEE, 2012, pp. 1–4.

[21] T. Hastie, S. Rosset, J. Zhu, and H. Zou, *Multi-class adaboost*, Statistics Interface **2** (2009), no. 3, 349–360.

[22] T.K. Ho, *Proceedings of 3rd international conference on document analysis and recognition*, IEEE, 1995, pp. 278–282.

[23] M.-L. Kaiser, J.-M. Albaret, and P.-A. Doudin, *Relationship between visual-motor integration, eye-hand coordination, and quality of handwriting*, J. Occupat. Therapy Schools Early Interven. **2** (2009), no. 2, 87–95.

[24] P.I. Khalid, J. Yunus, and R. Adnan, *Extraction of dynamic features from hand drawn data for the identification of children with handwriting difficulty*, Res. Dev. Disabil. **31** (2010), no. 1, 256–262.

[25] C. Kotsavasiloglou, N. Kostikis, D. Hristu-Varsakelis, and M. Arnaoutoglou, *Machine learning-based classification of simple drawing movements in Parkinson's disease*, Biomed. Signal Process. Control **31** (2017), 174–180.

[26] R.A. Langmaid, N. Papadopoulos, B.P. Johnson, J.G. Phillips, and N.J. Rinehart, *Handwriting in children with ADHD*, J. Atten. Disord. **18** (2014), no. 6, 504–510.

[27] J. Medwell and D. Wray, *Handwriting automaticity: The search for performance thresholds*, Language Educ. **28** (2014), no. 1, 34–51.

[28] J. Mekyska, M. Faundez-Zanuy, Z. Mzourek, Z. Galaz, Z. Smekal, and S. Rosenblum, *Identification and rating of developmental dysgraphia by handwriting analysis*, IEEE Trans. Human-Machine Syst. **47** (2016), no. 2, 235–248.

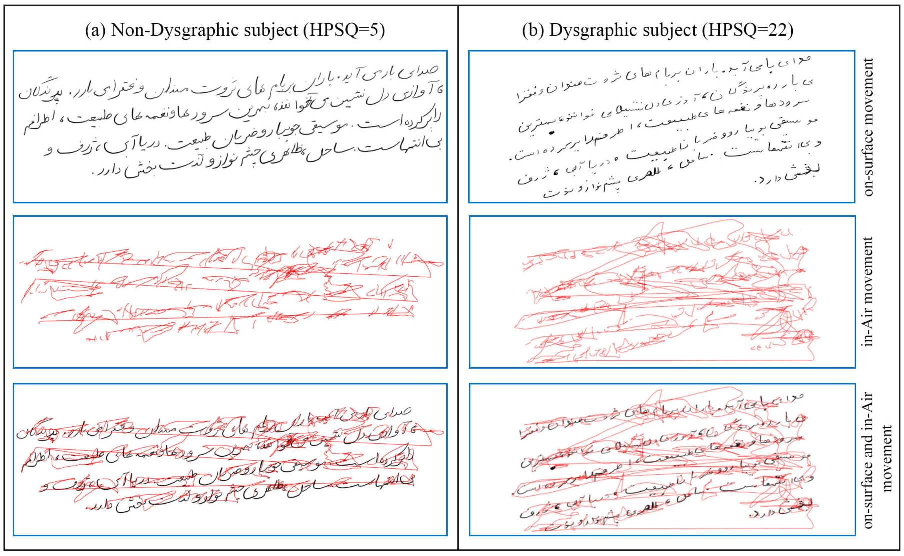


Figure 3: an example illustrating on-surface (black) and in-air (red) lines and both movements when writing a paragraph by children without (HPSQ=5) and with dysgraphia (HPSQ=22) from our database

[29] M. Moetesum, I. Siddiqi, N. Vincent, and F. Cloppet, *Assessing visual attributes of handwriting for prediction of neurological disorders—a case study on Parkinson's disease*, Pattern Recogn. Lett. **121** (2019), 19–27.

[30] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O.r Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, , and J. Vanderplas, *Scikit-learn: Machine learning in Python*, J. Machine Learn. Res. **12** (2011), 2825–2830.

[31] C.R. Pereira, S.A.T. Weber, C. Hook, G.H. Rosa, and J.P. Papa, *Deep learning-aided Parkinson's disease diagnosis from handwritten dynamics*, 29th Conf. Graph. Patterns Images (SIBGRAPI), IEEE, 2016, pp. 340–346.

[32] M.B. Racine, A. Majnemer, M. Shevell, and L. Snider, *Handwriting performance in children with attention deficit hyperactivity disorder (ADHD)*, J. Child Neuro. **23** (2008), no. 4, 399–406.

[33] S. Rosenblum and G. Dror, *Identifying developmental dysgraphia characteristics utilizing handwriting classification methods*, IEEE Trans. Human-Machine Syst. **47** (2016), no. 2, 293–298.

[34] Sara Rosenblum, *Development, reliability, and validity of the handwriting proficiency screening questionnaire (HPSQ)*, Amer. J. Occupat. Therapy **62** (2008), no. 3, 298–307.

[35] T.-Y. Shen, I.-H.and Lee and C.-L. Chen, *Handwriting performance and underlying factors in children with attention deficit hyperactivity disorder*, Res. Deve. Disabil. **33** (2012), no. 4, 1301–1309.

[36] M.H. Tseng and S.M.K. Chow, *Perceptual-motor function of school-age children with slow handwriting speed*, Amer. J. Occup. Therapy **54** (2000), no. 1, 83–88.

[37] M. Wallen, S. Duff, T.-A. Goyen, and E. Froude, *Respecting the evidence: Responsible assessment and effective intervention for children with handwriting difficulties*, Austr. Occupat. Therapy J. **60** (2013), no. 5, 366–369.

[38] Y. Wang and L. Feng, *An adaptive boosting algorithm based on weighted feature selection and category classification confidence*, Applied Intel. **51** (2021), no. 10, 6837–6858.

## Appendix

More examples of student handwriting (see Figure 3, Figure 4 and Figure 5).

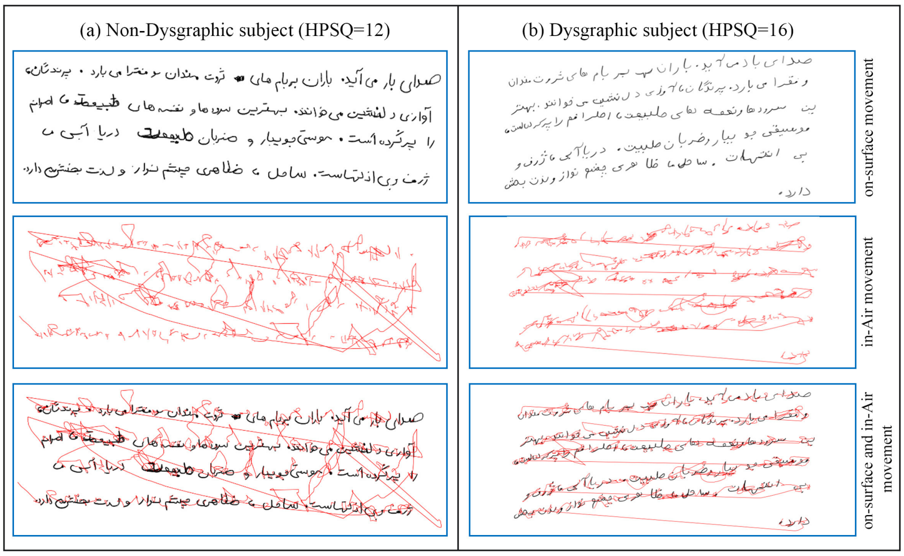


Figure 4: an example illustrating on-surface (black) and in-air (red) lines and both movements when writing a paragraph by children without (HPSQ=12) and with dysgraphia (HPSQ=16) from our database

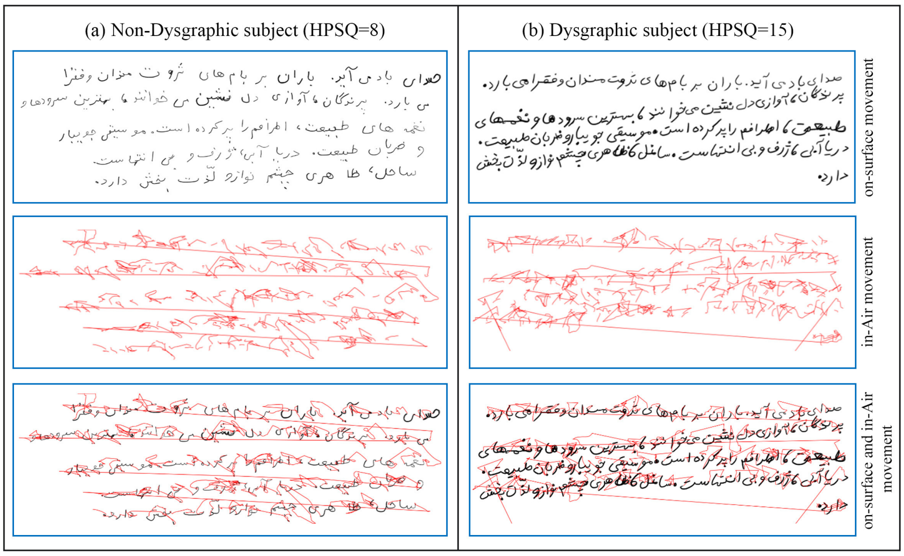


Figure 5: an example illustrating on-surface (black) and in-air (red) lines and both movements when writing a paragraph by children without (HPSQ=8) and with dysgraphia (HPSQ=15) from our database