DOI: 10.22146/jnteti.v14i1.16406

Digitized Cursive Handwriting for Determining FMS in Early School-Age Children

Nurul Zainal Fanani[1], Ika Widiastuti[2], Khamid[3], Laszlo T. Koczy[4]

[1] Mechatronics Engineering Technology Study Program, Department of Engineering, Politeknik Negeri Jember, Jember, Jawa Timur 68121, Indonesia
[2] Informatics Management Study Program, Department of Information Technology, Politeknik Negeri Jember, Jember, Jawa Timur 68121, Indonesia
[3] Department of Informatics Engineering, Faculty of Engineering, Universitas Wahidiyah, Kediri, Jawa Timur 64114, Indonesia
[4] Department of Informatics, Faculty of Mechanical Engineering, Informatics, and Electrical Engineering, Széchenyi István University, Egyetem tér 1, 9026 Győr, Hungary

[Received: 24 September 2024, Revised: 13 December 2024, Accepted: 3 February 2025]
Corresponding Author: Nurul Zainal Fanani (email: zainal_fanani@polije.ac.id)

ABSTRACT — Assessing fine motor skills (FMS) in early school-age children is crucial for insights into their school readiness. In many countries, including Indonesia, teachers assess FMS by observing handwriting, often with the aid of an educational psychologist. However, this approach can be subjective and prone to observer bias. This study aimed to classify children's FMS based on their cursive writing abilities using a digitizer to capture data. The system recorded data in real-time as children wrote in cursive, capturing the stylus's relative position on the digitizer board (including x, y, and z positions), and pressure values, which served as features in the classification process. The study involved 40 1st and 2nd-grade students from various elementary schools. The data recording process generated substantial raw datasets. The random forest algorithm, renowned for its effectiveness in analyzing large datasets, was employed for classification. The results demonstrated this method's efficacy in identifying FMS, achieving an accuracy rate of approximately 97.3%. This study concludes that integrating a digitizer with the random forest classification method provides a reliable and objective approach to assessing FMS in children, reducing observer bias, and ensuring precise results. In the long term, this approach can significantly enhance the accuracy of FMS assessments, enabling better-targeted interventions and support for children in need.

KEYWORDS — Assessment Using Digitizer, Fine Motor Skill, Random Forest, Digitized Cursive Handwriting.

I. INTRODUCTION

Fine motor skills (FMS) are the ability to coordinate movements of the small muscles from the limbs, especially those involving the fingers, for example, holding objects, writing, and cutting. FMS can be seen from the results of tests assessing someone's ability to complete tasks requiring finger movements with a specific level of accuracy. The higher the motor skills of a child, the more comfortable they will be in completing tasks with high accuracy. In general, a child's motor skills can be seen and compared with those of their peers. For example, 5-year-old children already sitting in kindergarten are generally able to write the letters of the alphabet. If they cannot write the alphabet letters, it could be because they have poor FMS. Children with good motor skills will quickly learn new things, which are very useful in education.

Utilizing FMS as an assessment of children's preparedness for school is crucial [1]. School readiness refers to a state where a child is prepared to engage effectively in the learning process at school. Numerous studies suggest that a child's writing proficiency can be indicative of their FMS level [2]. Consequently, teachers often gauge FMS by examining children's writing. For children in the early school years, particularly those in the 1st grade, educational psychologists assess their FMS by observing their hand scratches of writing results. These observations are then typically categorized into two groups: FMS appropriate for age (AG) and FMS less than age (LG).

One important indicator of school readiness is FMS [3]. These skills are essential for students' successful participant in learning activities in schools. FMS can be taught through sketching and writing activities. For most people, especially adults, writing is an easy task [4]. However, this can be a difficult task for children who start learning to write at an early school age, as it involves complex perceptual, cognitive, and motor processes [5].

Especially in handwriting, children must focus on holding a pencil and converting the letters into meaningful words simultaneously [6]. Children who improve their letter-writing skills and progress to more complex writing tasks require more integrated knowledge systems. These encompass the symbolic representation of a letter and being familiar with writing conventions [7]. There is a significant relationship between students' FMS in their early school years and their academic achievement [1]. It is suggested that copying images containing multiple shapes and using writing tools have a more significant impact on academic achievement. Handwriting and spelling significantly contributed to written expression in kindergarten. Prior study has confirmed that writing skills are among the essential FMS [8]. There is a significant relationship between children's early writing efforts and the development of their knowledge of how words construct meaning, and this is an important step toward academic achievement [9].

Children can optimally enhance their FMS by engaging in writing exercises, particularly cursive handwriting exercises. This requirement compels students to consider every writing detail. Cursive handwriting is a writing style that highlights the connections between letters and the relationships among syllables and word structures [10]. The use of cursive handwriting makes children more comfortable recognizing words. It also aligns with the development of their bodies and muscles. Prior study has emphasized the importance of teaching handwriting in schools [11]. Regular practice of cursive handwriting to increase writing and drawing speed can enhance handwriting performance [12].

In European countries, such as Italy, Spain, and Turkey, 1st-grade students are taught how to write using cursive handwriting. A researcher from Turkey has showed that cursive writing contributes to the student's cognitive development and helps improve their attention-related skills [10]. While there has been ongoing debate about handwriting instruction in recent years, research evidence continues to advocate for it, given its benefits in writing development. One of the advantages is that vertical writing aids in the development of FMS. Additionally, cursive handwriting allows for clearer separation of words and demands significantly more effort, activating brain regions involved in writing process [12]. The existing literatures have discussed the relationship between FMS and academic achievement. However, most literatures still focus on handwriting on papers.

There has been a rare discussion regarding the method of classifying FMS through the writing process by using computer aids. Previous research studied the handwriting process, investigating useful parameters for studying writing and learning development [13]. These kinematic parameters were obtained during the writing process using a digitizer. However, these parameters were not used to predict the FMS level. The Easy Sketch application has been developed to predict children's FMS levels using gesture-based features as a classification method and letters and shapes as objects of analysis. This application can automatically analyze children's sketches and classify the level of FMS sketches to help parents and teachers understand the strengths and weaknesses of children's drawing skills [4]. A similar model was successfully implemented in previous research, in which a model-free technique using a handwriting analysis tool to differentiate Parkinson's disease [14]. Despite differences in objectives among prior studies, they used the same handwritten feature extraction method proposed in [13]. A study utilized machine learning techniques to analyze handwriting to identify Parkinson's disease [15]. Another study also leveraged machine learning techniques to analyze handwriting sketches to detect children's FMS development [16].

As previously discussed, numerous methodologies have been employed in predicting FMS levels. However, the methodologies explored in these studies did not encompass the utilization of cursive handwriting as a predictive tool for FMS assessment. Despite the acknowledgment in several studies that manual writing can contribute to the enhancement of children's FMS, the primary objective of this study was to ascertain the viability of cursive handwriting as a means to classify FMS, which is an essential indicator of school readiness warranting attention from both educators and parents.

This study introduced a novel model for classifying FMS levels through the analysis of cursive handwriting processes. The research effort involved developing an intelligent system designed to capture and record data during the cursive writing sessions. The collected data encompassed various parameters of the stylus's movement on the digital board, including the x position (*x-pos*), y position (*y-pos*), z position (*z-pos*), and the pen pressure value (*p*). These data points served as crucial features for the subsequent classification process. This research is part of the study [17] that delves into outlier data from cursive writing.

Given the substantial volume of datasets generated during the cursive writing recording session, the study employed the random forest algorithm as the classification method. The utilization of this approach is rooted in a decision-making process that draws upon not just a single model, but multiple decision tree models generated at random from the dataset [16]. Numerous studies have demonstrated the effectiveness of the random forest method in classifying extensive datasets with incomplete attributes, often resulting in higher levels of accuracies compared to other alternative methods [18]. The system developed in this study harnessed an artificial intelligence technique to analyze these data, with the objective of intelligent FMS classification. This, in turn, lays the groundwork for teachers to effectively manage classroom learning dynamics.

The developed system developed aims to assist teachers in their observations to assess the FMS of each student. It is anticipated that by assessing these FMS, teachers can tailor the classroom environment to accommodate the conditions and characteristics of each student.

II. METHODOLOGY

This research is structured into four distinct stages: the preparatory, data recording, dataset collection, and FMS classification, as depicted in Figure 1.

A. PREPARATION

This stage is divided into two parts, which are carried out separately

1) CREATION OF THE DATA RECORDING SYSTEM

This stage encompassed both hardware and software components essential for the extraction and storage of data from digital boards into a database. The software was developed using C# language and encompassed a range of functionalities. These functionalities included recording of student and school information, such as age and gender. Additionally, the software could dynamically capture real-time data related to the position and pressure of the stylus on the digital board.

The data acquisition process occurred during writing activities performed on a digitizer, namely Wacom Cintiq 13HD. The application recorded the writing process with a sampling frequency of 220 Hz. The selection of this specific digital board was intended to offer participants a writing experience akin to writing on paper, while also priding the advantage of immediate visibility of the writing result. The digital board supplied a dataset comprising several values: *x-pos* within a range of 0–1.365, *y-pos* within a range of 0–767, *z-pos* within a range of 0–1.023, and *p* within a range of 0–1.023.

2) ASSESSMENT BY A PSYCHOLOGIST

This section is essential in research to gain insight into students' FMS estimates before they undergo observation during the writing process. During this phase, psychologists gave students specific instructions [19]. They employed a set of assessment tools designed to evaluate children's FMS [20]. The assessment, facilitated by the psychologists, utilized the Bender Gestalt instrument, as depicted in Figure 2. This assessment encompasses various aspects, including how to hold a pencil, control line drawing pressure, discern relative positions, and differentiate orientations when forming letters. Through these activities, educational psychologists assessed students' FMS by analyzing their handwriting strokes. The psychologists' evaluation resulted in a certificate that places the students' FMS condition into FMS AG and FMS LG. The

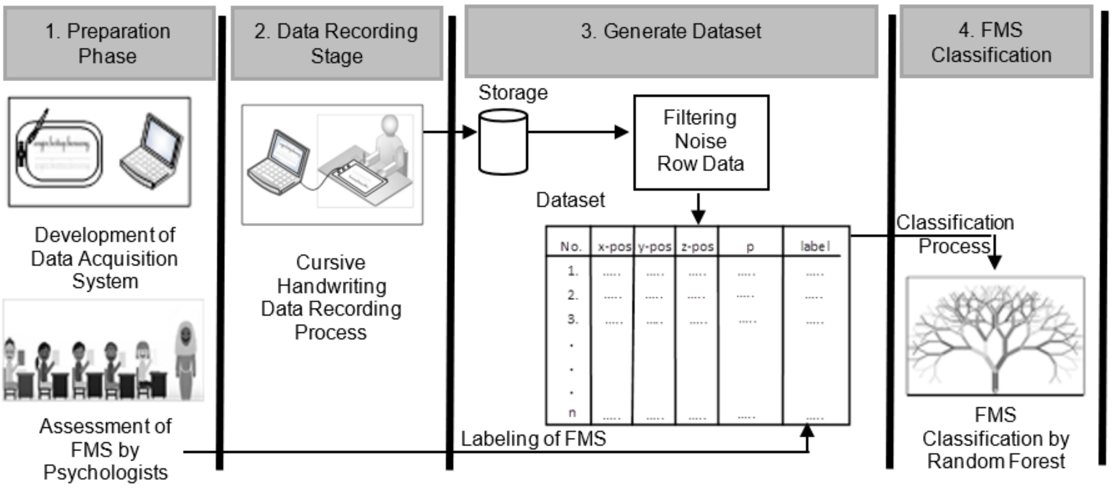


Figure 1. Proposed method for determining FMS.

Figure 2. Assessment by a psychologist.

psychologists' observations culminated in classifying students based on their FMS.

B. DATA RECORDING

This stage involved the data collection process, during which students were asked to write cursive letters. From an initial group of 110 1st and 2nd-grade students assessed by a psychologist, 40 were randomly selected to participate for this experiment. These included 20 1st-grade students: 10 with FMS AG and 10 with FMS LG. Similarly, ten students from each category (FMS AG and FMS LG) were selected from 2nd-grade students. These samples were deemed representative of the participant population across the three schools, as detailed in Table I. Notably, no 1st-grade students in School 2 were identified as having FMS LG during the psychologist's assessment.

The students who participated in this study were drawn from three elementary schools in Jember, Jawa Timur, each characterized by distinct attributes. School 1 is SDN Bintoro 5. It is situated in the Patrang subdistrict of Jember, Jawa Timur. This school is nestled in a remote mountainous area, where most students' parents are engaged in coffee plantation work and have lower levels of education. Importantly, none of the students in School 1 have access to electronic devices. School 2 is SDN Karangrejo 6, which is located in the Sumbersari subdistrict of Jember, Jawa Timur. This school is relatively closer to the city center, and most of the students' parents are

TABLE I
RESEARCH PARTICIPANTS DISTRIBUTION

Grade	Label	Number of Students in the School 1	Number of Students in the School 2	Number of Students in the School 3	Total of Students
First grade	AG	1	4	5	10
	LG	4	0	6	10
Second grade	AG	3	4	3	10
	LG	3	3	4	10

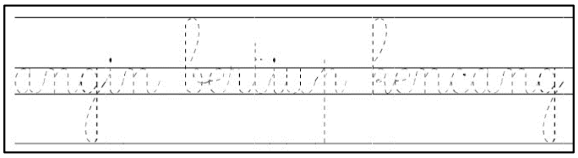
involved in agricultural labor and vegetable trading, with their educational backgrounds generally limited to middle school. Only a few students in School 2 have access to electronic gadgets. School 3 is SDN Karangrejo 2. It is positioned in close proximity to the city center. Here, most parents are employed in formal sectors, possessing educational qualifications of at least a high school. Nearly all students in School 3 possess electronic gadgets.

This experiment involved the design of two tasks that students from 1st and 2nd grade must complete to validate the proposed approach (Figure 3). In task 1, students were tasked with emboldening the sentence "angin bertiup kencang" (the wind is blowing hard), while in task 2, students were instructed to replicate a sentence while applying cursive writing on a dotted line. This choice is substantiated by the fact that 1st-grade students are still in the process of learning to write basic letters and may not have a comprehensive understanding of the concept of cursive writing. In contrast, 2nd grade students typically have a stronger grasp of cursive letters.

The experimental assignment adhered to the initial reading and writing guidelines set forth by the Ministry of Education and Culture of the Republic of Indonesia. Task 1 involved enhancing the cursive sentence "angin bertiup kencang," as depicted in Figure 4(a). Students were instructed to replicate the sentences on a paper template using the digitizer board. Task 2 entailed the completion of cursive writing by copying sentences rendered with dotted lines, as illustrated in Figure 4(b). The objective of task 2 was to gain insights into students' perceptions of cursive writing and their ability to execute it. The system that was developed recorded data points such as the *x-pos*, *y-pos*, *z-pos*, and *p*, which were subsequently saved into a .csv file for future use as a dataset.

Figure 3. Data recording process.

(a)



(b)

Figure 4. Experimental assignments, (a) task 1: students are asked to bold the sentence and (b) task 2: students are asked to copy a word or sentence and apply cursive writing in a dotted line.

C. DATA COLLECTION

In the developed application, a digital board was utilized to capture multiple signals. These signal encompass the position of the nib in the *x-pos*, *y-pos*, and *z-pos* coordinates, denoted as *x-pos* = { *x-pos*1, *x-pos*2, *x-pos*3 ..., *x-posi* ..., *x-posn*}, *y-pos* = { *y-pos*1, *y-pos*2, *y-pos*3 ..., *y-posi* ..., *y-posn*}, *z-pos* = { *z-pos*1, *z-pos*2, *z-pos*3 ..., *z-posi* ..., *z-posn*} and the pen tip pressure exerted on the digital board represent as $p = \{p1, p2, p3 \ldots, pi \ldots, pn\}$. In addition to capturing pen position, the digital board is also capable of registering the intensity of pen pressure applied against its surface. These captured signals—*x-pos*, *y-pos*, *z-pos*, and *p*—served as features for the classification process, enabling the analysis of handwriting patterns. This supplementary information adds significant value to overall handwriting analysis [4].

The coordinate range along the x-axis spans from 0–1,365. During the recording of the writing process data for this study, the assignment template was positioned with x_{min} = 364 and x_{max} = 990, as depicted in Figure 5. Here, x_{min} represents the leftmost coordinate of the template in the relation to the x-axis on the digital board, while x_{max} is the rightmost coordinate of the assignment template on the digitizer board.

The raw data obtained during the data collection process underwent a noise-filtering procedure. Data points outside the range defined by x_{min} and after x_{max} along the *x-pos*, *y-pos*, *z-pos*, and *p* axes were omitted. This filtering process generated a new dataset comprising refined *x-pos*, *y-pos*, *z-pos*, and *p* values. The refined data were then combined with the FMS labels obtained from psychological assessments for each student. This combination resulted in the creation of a comprehensive dataset, as illustrated in Table II. The dataset was subsequently processed using the proposed classification method.

Figure 5. Coordinate mapping x, y and z on board.

TABLE II
EXAMPLES OF DATASET FOR TASK 1 ON THE CURSIVE WRITING PROCESS IN FIRST GRADE

No.	*x-pos*	*y-pos*	*z-pos*	*p*	Label
1	364	506	0	236	AG
2	364	506	0	234	AG
3	364	506	0	229	AG
4	365	507	0	234	AG
5	365	507	0	235	AG
.	.	.	.	.	.
.	.	.	.	.	.
392919	990	490	0	317	LG
392920	990	490	0	315	LG
392921	990	490	0	317	LG
392922	990	490	0	318	LG
392923	990	490	0	316	LG

The dataset derived from this phase encapsulates the knowledge gleaned during the writing process utilizing a digitizer. In the pedagogy of writing, teacher observe several key components: the pressure applied by students when using the pencil, the duration of writing session, the promptness with which students commence writing, and the frequency with which they lift their pencil from the paper. These components serve as a reference point for teachers in assessing children's FMS, determining whether they align with age-appropriate expectations or fall below the expected level.

These observed components are instrumental in extracting insights for the evaluation of children's FMS. Information within the dataset generated from this stage mirrors the components observed by the teachers during the cursive writing learning process in the school environment.

For each writing process of every participant, all datasets were categorized based on the assessment results provided by the psychologist, classifying participants into either the FMS AG or the FMS LG category. This labeling by psychologists serves as the foundation of the dataset's integrity. As a result, the dataset was derived from the writing processes of 10 students with FMS AG and 10 students with FMS LG for each grade level. The assignments encompassed *x-pos*, *y-pos*, *z-pos*, and *p* features; these labels served as the fundamental components for knowledge discovery.

D. FMS CLASSIFICATION

In this classification stage, three experiments were prepared to assess the accuracy of FMS classification in the cursive writing process. The classification methods employed include random forest [21], [18]; k-nearest neighbor (KNN) [22]; and naïve Bayes [23].

Random forest, also known as random decision forest, utilizes ensemble learning. Ensemble learning is a predictive approach that involves multiple stages of learning. Within the realm of ensemble learning, random forest incorporates algorithms such as bootstrap aggregation, commonly referred to as bagging. Moreover, it incorporates regression methods and entails the construction of multiple decision trees using (1).

$$\hat{f} = \frac{1}{B}\sum_{b=1}^{B} f_b(x'). \quad (1)$$

The training set is represented as X, and the response is denoted by Y, with bagging repetition is indicated as $\sum_{b=1}^{B}$. The total number of training data instances is denoted as n. Samples drawn with replacement are represented as X_b, Y_b. Within X_b, Y_b, a regression tree is denoted as f_b. After the training process, the prediction is represented as x'.

The KNN algorithm is a nonparametric method employed for both classification and regression tasks within the classification process. In both scenarios, the algorithm identifies the k-nearest training instances within the feature space. The nature of the output depends on whether KNN is used for classification or regression.

In KNN classification, the output pertains to the class membership of an object. The object is classified based on the majority class among its KNN within the feature space. Typically, k is a positive integer, often kept small. When k = 1, the object is assigned to the class of its closest neighbor. Conversely, in KNN regression, the output represents the property value associated with the object. This value is computed as the average of the k property values derived from its nearest neighbors. KNN is a form of example-based learning, often referred to as “lazy” learning, where functions are locally approximated, and computations are deferred until the classification stage. It is applicable to both classification and regression tasks.

A notable technique in KNN involves assigning weights to the contribution of neighbors. In this scheme, closer neighbors exert a greater influence on the average calculation compared to those farther away. A common weighting scheme assigns a weight of *1/d* to each neighbor, with *d* signifying the distance to the neighbors. The neighbors used in KNN are drawn from a dataset containing objects with known class labels (for KNN classification) or known property values (for KNN regression). This dataset serves as the training data for the algorithm, although KNN does not explicitly require a formal training step [22]. KNN operates by utilizing a distance matrix, often based on the Euclidean distance, as exemplified in (2).

$$d(e,f) = \sqrt{\sum_{i=1}^{n}(e_i - f_i)^2} \quad (2)$$

where $d(e,f)$ is the distance between the features being compared into groups to a particular label, n is the amount of data. The total data is $E = (e_i, \ldots, e_n)$.

Naïve Bayes is a probabilistic classifier that works based on Bayes’ rules using (3).

$$p(C_k|v) = \frac{p(v|C_k)p(C_k)}{p(v)} \quad (3)$$

TABLE III
CLASSIFIER COMPARISON

Classification Methods	First Grade		Second Grade	
	Task 1 (%)	***Task 2 (%)***	***Task 1 (%)***	***Task 2 (%)***
Random forest	97.3	95.3	95.3	95.9
KNN	95.2	92.5	92.5	93
Naïve Bayes	61.5	61.6	61.5	56.5

TABLE IV
CONFUSION MATRIX TO SHOW THE PROPORTION OF PREDICTION OF TASK 1 IN FIRST-GRADE STUDENTS USING RANDOM FOREST, KNN, NAÏVE BAYES

	Predicted Random Forest (%)		Predicted KNN (%)		Predicted Naïve Bayes (%)	
	AG	***LG***	***AG***	***LG***	***AG***	***LG***
Actual AG (%)	96.9	2.3	94.0	3.8	56.3	34.7
Actual LG (%)	3.1	97.7	6.0	96.2	43.7	65.3

where v is a vector of the feature and C_k is the possible label generated from k. The equation can be written as in (4).

$$Posterior = \frac{prior \times likelihood}{evidence}. \quad (4)$$

III. RESULTS AND DISCUSSION

The classification results using random forest, KNN, and naïve Bayes classifiers for each task completed by 1st and 2nd-grade students are presented in Table III. The random forest method consistently demonstrated the highest accuracy across all classes and assignments, yielding the highest score of 97.3% for 1st-grade students in task 1 and 95.9% for 2nd-grade students in task 2. These results surpassed KNN by approximately 2.1% for 1st-grade students in task 1 and approximately 2.9% for 2nd-grade students in task 2. There was a substantial performance gap of approximately 35.8% in favor of random forest over the naïve Bayes method for 1st-grade students in task 1 and approximately 39.4% in favor of random forest for 2nd-grade students in task 2.

In general, random forest classifier consistently outperformed the other two classifiers, namely KNN and naïve Bayes, across assignments and classes. The naïve Bayes classification exhibited lower predictive accuracy, achieving a maximum of 61.6% in 1st-grade students for task 2 and a minimum of 56.5% in 2nd-grade students in task 2. On average, the random forest and KNN outperformed naïve Bayes by a significant margin of approximately 40% across all assignments and classes.

The results of the experiments conducted with 1st-grade students in task 1 are detailed in Table IV. The random forest classifier yielded an accuracy rate of 96.9% for AG and 97.7% for LG, indicating high accuracy in labeling suitability. Similarly, the KNN classifier produced an accuracy rate of 94% for AG and 96.2% for LG, demonstrating comparable results to the random forest classifier. In contrast, the naïve Bayes classifier achieved a lower accuracy rate of 56.3% for AG and 65.3% for LG.

Furthermore, the results of the 2nd-grade student test with task 2, as presented in Table V, were compared with those of the 1st-grade test with task 1. In the second experiment, the random forest classifier yielded a slightly lower accuracy at approximately 95.5% for AG and 96.4% for LG. Nevertheless,

p-ISSN 2301–4156 | e-ISSN 2460–5719

TABLE V
CONFUSION MATRIX TO SHOW THE PROPORTION OF PREDICTION OF TASK 2 IN SECOND-GRADE STUDENTS USING RANDOM FOREST, KNN, NAÏVE BAYES

	Predicted Random Forest (%)		Predicted KNN (%)		Predicted Naïve Bayes (%)	
	AG	***LG***	***AG***	***LG***	***AG***	***LG***
Actual AG (%)	95.5	3.6	91.5	5.6	51.7	42.1
Actual LG (%)	4.5	96.4	8.5	94.4	48.3	57.9

it maintains its dominance in accuracy over the other two classifiers. The KNN classifier also exhibited a decreased accuracy compared to the 1st-grade experiment, with an accuracy rate of 91.5% for AG and 94.4% for LG. Similarly, the naïve Bayes classifier showed a decline in accuracy in the second experiment, achieving an accuracy rate of 51.7% for AG and 57.9% for LG. The difference is significant when compared to the previous two classifiers, random forest and KNN, with a decrease of approximately 30% for both AG and LG.

IV. CONCLUSION

The proposed method has demonstrated superior accuracy in predicting childhood FMS compared to other classification methods. The random forest classifier proves highly suitable for assessing FMS in both 1st and 2nd-grade elementary school students, achieving remarkable accuracy of up to 97.3%.

Future research will explore advanced feature extraction techniques and hybrid models that integrate multiple algorithms to potentially improve classification accuracy. Additionally, transfer learning is aimed to be investigated, and custom-designed architectures tailored specifically to handwriting features are planned to be developed, further improving the system's performance and its contribution to the field.

AUTHORS' CONTRIBUTIONS

Conceptualization, Nurul Zainal Fanani; methodology, Laszlo T. Koczy; software, Khamid; validation, Ika Widiastuti and Nurul Zainal Fanani; formal analysis, Nurul zainal Fanani; investigation, Ika Widiastuti; resources, Ika Widiastuti; data curation, Khamid and Nurul Zainal Fanani; writing—original draft preparation, Ika Widiastuti and Nurul Zainal Fanani; writing—review and editing, Laszlo T. Koczy; visualization, Nurul Zainal Fanani; supervision, Ika Widiastuti; project administration, Nurul Zainal Fanani; funding acquisition, Nurul Zainal Fanani and Ika Widiastuti.

REFERENCES

[1] D. Grissmer *et al.*, "Fine motor skills and early comprehension of the world: Two new school readiness indicators," *Dev. Psychol.*, vol. 46, no. 5, pp. 1008–1017, Sep. 2010, doi: 10.1037/A0020104.

[2] S.-M. Seo, "The effect of fine motor skills on handwriting legibility in preschool age children," *J. Phys. Ther. Sci.*, vol. 30, no. 2, pp. 324–327, Feb. 2018, doi: 10.1589/jpts.30.324.

[3] K.P. Feder and A. Majnemer, "Handwriting development, competency, and intervention," *Dev. Med. Child Neurol.*, vol. 49, no. 4, pp. 312–317, Apr. 2007, doi: 10.1111/J.1469-8749.2007.00312.x.

[4] H. Kim, S. Valentine, P. Taele, and T. Hammond, "EasySketch: A sketch-based educational interface to support children's self-regulation and school readiness," in *The Impact of Pen and Touch Technology on Education*. Cham, Swiss: Springer, 2015.

[5] H.K. Gerde, T.D. Foster, and L.E. Skibbe, "Beyond the pencil: Expanding the occupational therapists' role in helping young children to develop writing skills," *Open J. Occup. Ther.*, vol. 2, no. 1, pp. 1–19, Jan. 2014, doi: 10.15453/2168-6408.1070.

[6] H. Schwellnus *et al.*, "Effect of pencil grasp on the speed and legibility of handwriting in children," *Am. J. Occup. Ther.*, vol. 66, no. 6, pp. 718–726, Nov./Dec. 2012, doi: 10.5014/ajot.2012.004515.

[7] C.S. Puranik and C.J. Lonigan, "From scribbles to scrabble: Preschool children's developing knowledge of written language," *Read. Writ.*, vol. 24, no. 5, pp. 567–589, May 2011, doi: 10.1007/S11145-009-9220-8/tables/8.

[8] C.S. Puranik and S. Alotaiba, "Examining the contribution of handwriting and spelling to written expression in kindergarten children," *Read. Writ.*, vol. 25, no. 7, pp. 1523–1546, Aug. 2012, doi: 10.1007/s11145-011-9331-x.

[9] C. Zhang, J. Hur, K.E. Diamond, and D. Powell, "Classroom writing environments and children's early writing skills: An observational study in head start classrooms," *Early Child. Educ. J.*, vol. 43, no. 4, pp. 307–315, Jul. 2015, doi: 10.1007/S10643-014-0655-4.

[10] T. Erdogan and O. Erdogan, "An analysis of the legibility of cursive handwriting of prospective primary school teachers," in *4th World Conf. Educ. Sci. (WCES-2012)*, 2012, pp. 5214–5218, doi: 10.1016/j.sbspro.2012.06.412.

[11] E.S. Oche, "The influence of poor handwriting on students' score reliability in mathematics," *Math. Educ. Trends Res.*, vol. 2014, pp. 1–15, Jan. 2014, doi: 10.5899/2014/metr-00035.

[12] A. Comajuncosas, M. Faundez-Zanuy, J. Solé-Casals, and M. Portero-Tresserra, "Preliminary study on implications of cursive handwriting learning in schools," in *Multidisciplinary Approaches to Neural Computing*. Cham, Switzerland: Springer, 2018.

[13] A.P. Accardo, M. Genna, and M. Borean, "Development, maturation and learning influence on handwriting kinematics," *Hum. Mov. Sci.*, vol. 32, no. 1, pp. 136–146, Feb. 2013, doi: 10.1016/j.humov.2012.10.004.

[14] V. Bevilacqua *et al.*, "A model-free computer-assisted handwriting analysis exploiting optimal topology ANNs on biometric signals in parkinson's disease research," in *14th Int. Conf. Intell. Comput. Theor. Appl. (ICIC 2018)*, 2018, pp. 650–655, 2018.

[15] M. Moetesum, I. Siddiqi, F. Javed, and U. Masroor, "Dynamic handwriting analysis for Parkinson's disease identification using C-BiGRU model," in *2020 17th Int. Conf. Front. Handwrit. Recognit. (ICFHR)*, 2020, pp. 115–120, doi: 10.1109/icfhr2020.2020.00031.

[16] S. Polsley *et al.*, "Detecting children's fine motor skill development using machine learning," *Int. J. Artif. Intell. Educ.*, vol. 32, no. 4, pp. 991–1024, Dec. 2022, doi: 10.1007/s40593-021-00279-7.

[17] N.Z. Fanani *et al.*, "Two stages outlier removal as pre-processing digitizer data on fine motor skills (FMS) classification using covariance estimator and isolation forest," *Int. J. Intell. Eng. Syst.*, vol. 14, no. 4, pp. 571–582, Aug. 2021, doi: 10.22266/ijies2021.0831.50.

[18] A. Zakrani, M. Hain, and A. Namir, "Software development effort estimation using random forests: An empirical study and evaluation," *Int. J. Intell. Eng. Syst.*, vol. 11, no. 6, pp. 300–311, Dec. 2018, doi: 10.22266/ijies2018.1231.30.

[19] M. Longcamp, M.-T. Zerbato-Poudou, and J.-L. Velay, "The influence of writing practice on letter recognition in preschool children: A comparison between handwriting and typing," *Acta Psychol.*, vol. 119, no. 1, pp. 67–79, May 2005, doi: 10.1016/j.actpsy.2004.10.019.

[20] E.M. Koppitz, *The Bender Gestalt Test for Young Children*. New York, NY, USA: Grune & Stratton, 1964.

[21] N. Zainal, A.G. Sooai, S. Sumpeno, and M.H. Purnomo, "Children's fine motor skill determination from Hanacaraka writing process using random forest," *J. Nas. Tek. Elekt. Teknol. Inf.*, vol. 9, no. 2, pp. 148–154, May 2020, doi: 10.22146/JNTETI.V9I2.153.

[22] A. Mucherino, P.J. Papajorgji, and P.M. Pardalos, "K-nearest neighbor classification," in *Data Mining in Agriculture*. New York, NY, USA: Springer, 2009.

[23] K.P. Murphy, "A Probabilistic Perspective," in *Chance Encounters: Probability in Education*. Dordrecht, Netherlands: Springer, 1991.