VISVESVARAYA TECHNOLOGICAL UNIVERSITY
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A synopsis on

Detection of SLD in Kannada Vocabulary amongst Undergraduate Students

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Under the Guidance of

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1. Abstract

This study introduces an innovative method for identifying Slow Learning Disability (SLD) in Kannada Vocabulary among undergraduate students, utilizing Convolutional Neural Networks (CNN) and Random Forest classifiers. By digitizing handwritten words from sheets, analyzing features such as writing pressure, bounding box dimensions, and character spacing, our approach achieves a 72.79% accuracy with CNN and a 74.26% accuracy with Random Forest. This method surpasses previous techniques, which were cumbersome for students, costly, required physical intervention and specific hardware. Our technique simplifies the process by scanning handwritten sheets, which are then processed to classify them as Normal or Abnormal. Additionally, it has been observed that students with low writing pressure showed lesser desire to learn, and students with higher writing pressure showed more desire to learn. Furthermore, it has been observed that students with larger handwriting were mostly classified as normal, and students with smaller handwriting were mostly classified as abnormal. This research offers a more user-friendly and affordable solution for SLD detection, potentially enhancing early support for at-risk students.

2. Introduction

2.1 Overview

Even with technology getting better, writing by hand is still really important. Talking with others, and showing how you feel. But, some people have a hard time writing neatly and easily due to slow learning disabilities. This makes it tough for them to communicate, express themselves, and capture their ideas. This problem affects 12-33% of kids in school [1]. It can make it hard for them to do well in school, feel good about themselves. It's really important to find out about this problem and get help.

2.2 Motivation

Witnessing the struggles faced by young children with slow learning disabilities, particularly within the Kannada-speaking community, inspired us to undertake this research. Existing solutions are often time-consuming, expensive, and lack specific support for diverse languages and cultural backgrounds. By developing a novel, cost-effective, and user-friendly technology, we aim to make detection of slow learning disabilities more accessible and effective for all. Our hope is to remove barriers to learning.

2.3 Objective

- This initiative addresses the lack of existing solutions specifically tailored to the Kannada language and leverages machine learning techniques to improve the accuracy and efficiency of slow learning disability assessments.

Key objectives include:

- **Developing an automated system:** This system will utilize machine learning algorithms to analyze handwriting samples and identify potential slow learning disability symptoms in Kannada-speaking children.
- **Handwriting feature identification:** Key handwriting features essential for identifying slow learning disability are size, pressure and letter characteristics, will be identified and analyzed.

2.4 Scope

A Machine learning model which is trained on a dataset collected from undergraduate students, capable of assessing the probability of a given person having a slow learning disability based on the features detected in their handwriting.

To complete the project within a timeframe of nine months, including four months for research and algorithm development, two months for system implementation and testing, and three months for analysis, optimization, and documentation.

2.5 Existing System

Despite the increasing prevalence of slow learning disability, particularly in developing countries like India, existing systems for its detection face significant limitations. Notably, most research and development efforts have focused on Western languages, neglecting languages like Kannada.

Furthermore, existing systems often rely on expensive technologies like iPads [3] and digital tablets [4], [5] with styluses for handwriting analysis. This creates accessibility barriers for resource-constrained families and limits the scalability of such solutions. Additionally, these systems often use proprietary apps that are not open-source or publicly accessible, raising concerns about transparency and applicability.

While some researchers have explored camera-based methods for detection, these approaches have not yet achieved the high accuracy levels which are often due to limitations in camera resolution, lighting conditions, and the ability to capture subtle handwriting details necessary for accurate analysis, making them unsuitable for classification.

2.6 Proposed System

To address the limitations of existing slow learning disability detection systems, we've built a novel approach specifically for Kannada handwriting. Unlike systems reliant on expensive tablets, our system will be accessible and affordable. We've also acquired Kannada-specific data from undergraduate students of BMSCE. These students wrote 21 Kannada words on an A4 sheet divided into grid boxes for consistent data capture.

After collecting the dataset or the assessment sheet from the student, the sheet must immediately undergo a pressure test. In this pressure test we feel the back of the handwritten words and check the pressure put on by the person writing the words. By assessing the pressure we put it into one of the three categories, which is High pressure, Medium pressure and Low pressure. After classifying the assessment based on the pressure, the assessment sheet is scanned for the next step in the assessment process. The scanned sheet is fed into an opencv function which will crop out all the 21 words written by the person. All the 21 words were chosen such that they cover all the words in Kannada language.

For analysis, we propose a CNN and random forest model. This model, trained on our pre-processed data, will predict a score for each writing sample. We'll then categorise these scores into two levels: Normal, and Abnormal. This classification system provides a comprehensive assessment of handwriting fluency and legibility, making slow learning disability identification easier and more reliable.

3. Design

3.1 High Level Design

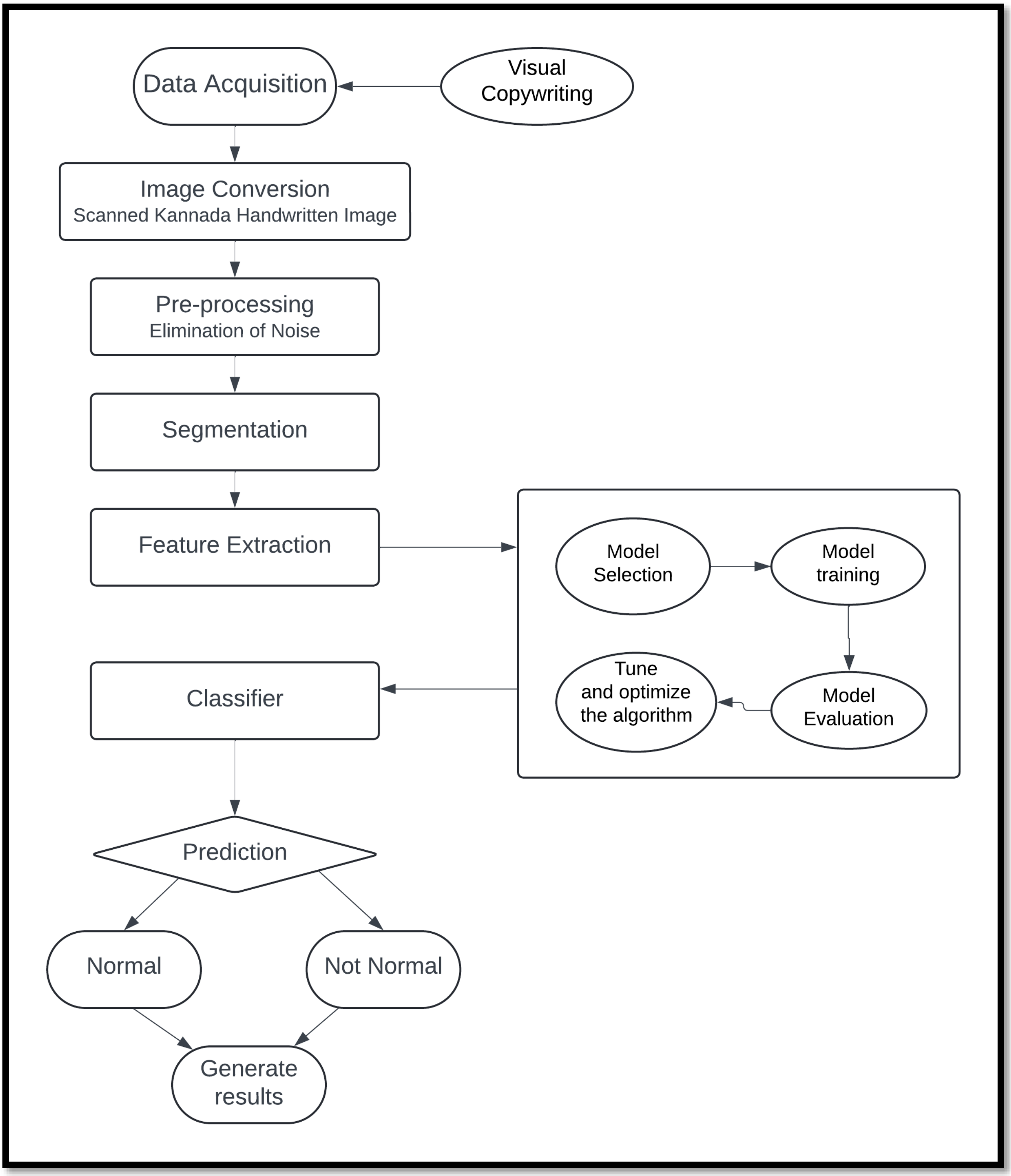

Figure 1. High Level Design of SLD Detection System

Figure 1 briefly mentions the high-level design and methodology for an automated dysgraphia detection system in primary and middle school children. It utilizes various image processing techniques and feature extraction methods to analyze handwritten Kannada characters and identify potential probability of having slow learning disability.

3.2 System Architecture

Each sub-system within the architecture performs a specific task with defined inputs and outputs. Their detailed specifications can be found in the methodology.

1. **Data Acquisition**:
    - A dataset specific to Kannada is compiled from undergraduate students of BMSCE. These students copied 21 words on an A4 sheet, systematically divided into grid boxes to ensure consistent data capture.

2. **Data pre-processing:**
    - Canny edge detection algorithm is applied to grayscale images for contour analysis, capturing sharp transitions between Kannada character strokes effectively.
    - Grid-based image cropping extracts pertinent writing regions from A4 sheets. Denoising techniques like grayscale conversion simplify image processing by removing irrelevant colour information while retaining essential stroke and shading details.
    - Gaussian blur smoothens the image, reducing isolated pixel variations and improving edge consistency. Thresholding eliminates undesired artifacts by binarizing images to clearly differentiate strokes from the background. Pressure is labelled using manual methods for each of the extracted image box.

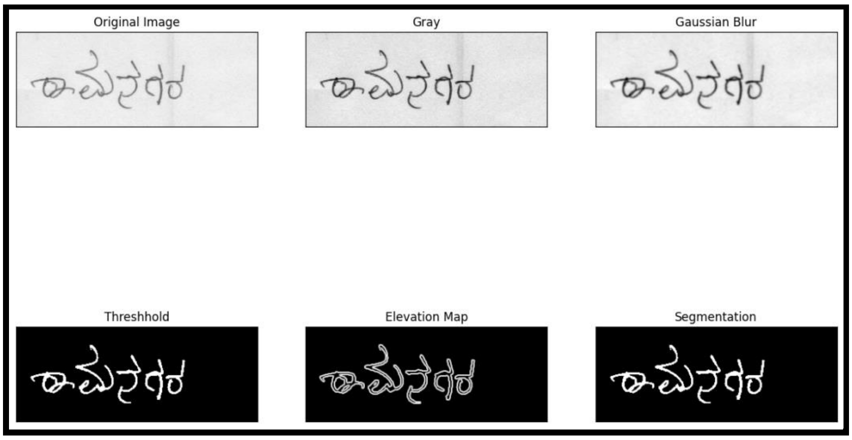

Figure 2. Filters applied on the cropped image

3. **Feature identification:**
   - The following six features are chosen as they can be easily identified and analysed by the handwriting analysis - pressure, height and length of the word, skew of the written word, height, length and distance between each character in a word.
   - Watershed algorithm is applied to threshold grayscale images with predefined markers to extract each character from the whole word. Watershed effectively handles touching or overlapping characters by identifying valleys between strokes as segmentation points.
   - These features are extracted by drawing the bounding boxes and contours around each character in the word and taking the highest and lowest points of each character.

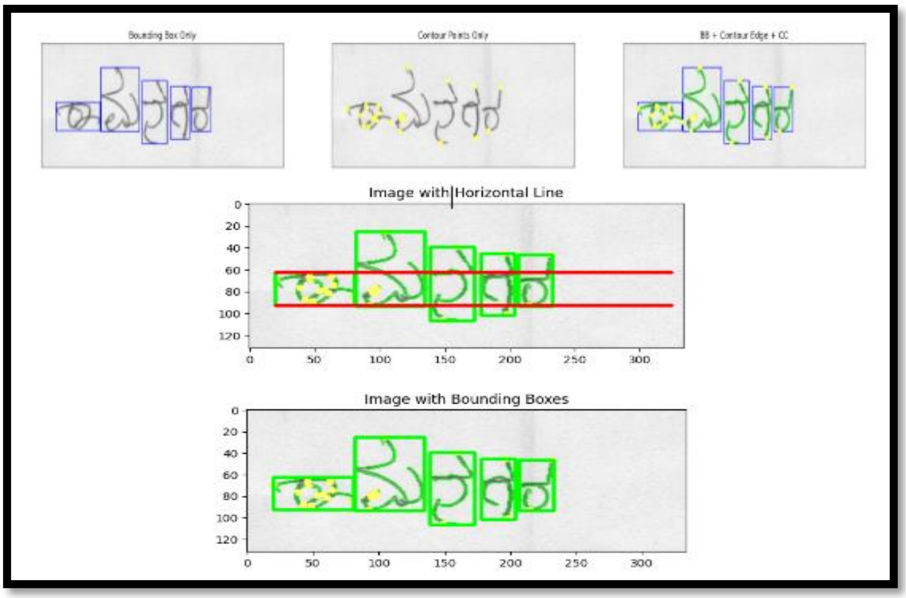

Figure 3. Cropped image with contours and feature points

Sl.No	Char	Bounding Box	Char Width	Character Height	Character Gaps	Word Width	Word Height	Skewed Angle	ClassId
0	Char_1	(56, 55, 39, 36)	39	36	4	87	10	[7.1134853]	0
1	Char_2	(99, 58, 42, 27)	42	27	2	87	10	[7.1134853]	0
2	Char_3	(143, 65, 20, 18)	20	18	2	87	10	[7.1134853]	0
3	Char_1	(56, 55, 39, 36)	39	36	4	87	10	[1.1134853]	0
4	Char_2	(99, 58, 42, 27)	42	27	2	87	10	[1.1134853]	0

Figure 4. Sample features extracted from the dataset

4. Model selection:

1. CNN [19-20] model is used to train on the dataset. CNN is used because of its power to identify the features from images.
2. Random forest classification is used to perform classification.

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 64, 112, 112]	1,792
MaxPool2d-2	[-1, 64, 56, 56]	0
ReLU-3	[-1, 64, 56, 56]	0
Conv2d-4	[-1, 192, 56, 56]	110,784
MaxPool2d-5	[-1, 192, 28, 28]	0
ReLU-6	[-1, 192, 28, 28]	0
Conv2d-7	[-1, 384, 28, 28]	663,936
ReLU-8	[-1, 384, 28, 28]	0
Conv2d-9	[-1, 256, 28, 28]	884,992
ReLU-10	[-1, 256, 28, 28]	0
Conv2d-11	[-1, 256, 28, 28]	590,080
MaxPool2d-12	[-1, 256, 14, 14]	0
ReLU-13	[-1, 256, 14, 14]	0
Dropout-14	[-1, 25088]	0
Linear-15	[-1, 1000]	25,089,000
ReLU-16	[-1, 1000]	0
Dropout-17	[-1, 1000]	0
Linear-18	[-1, 256]	256,256
ReLU-19	[-1, 256]	0
Linear-20	[-1, 43]	11,051

```
Total params: 27,607,891
Trainable params: 27,607,891
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.57
Forward/backward pass size (MB): 10.15
Params size (MB): 105.38
Estimated Total Size (MB): 116.10
```

Figure 5. CNN model architecture

4. Implementation

4.1 Overview of Technologies Used

Technologies used include:

- Google Colab: This free Jupyter notebook environment lets you train complex models in the cloud. It provides access to powerful GPUs, making tasks like training deep learning models on large datasets much faster and more accessible. We used Colab for training all our models.
- Google Drive: This cloud storage platform keeps your data safe and readily available. It simplifies file sharing and collaboration, allowing teams to work together seamlessly. We used Google Drive to store our datasets and trained models.
- Python: As a high-level, interpreted language, Python is known for its readability and ease of use. It supports various programming paradigms like object-oriented, functional, and procedural, making it versatile for different project needs. Python's extensive ecosystem of machine learning libraries makes it a favorite for such projects.
- OpenCV: This open-source computer vision library played a crucial role in our project. We used OpenCV for image processing tasks like extracting features (parameters) from individual letters in images. This prepared the data for further analysis by other libraries.
- TensorFlow: This open-source library underpins various machine learning applications, including neural networks. Its use of data flow graphs and differentiable programming allows for efficient model development and training.
- Keras: Built on top of TensorFlow, Keras is a high-level neural network API. It simplifies the creation and experimentation with deep learning models thanks to its modular design.

4.2 Implementation details of modules

The process begins with the extraction module, which navigates through a folder containing all the scanned sheets and cropping each grid box into individual files. This is followed by pre-processing, which involves various techniques such as Canny edge, watershed, denoising, Gaussian blur, thresholding, elevation maps, contour points, segmentation, baseline characteristics, among others.

Once the pre-processing is complete, the OpenCV2 module takes each image as an individual input and extracts the required data from it. This includes the character width and height, word width and height, inter-character spacings, and skew angle. All of these characteristics are then compiled into a dataframe, which stores all the metrics in a serial order. This dataframe is subsequently converted into a csv file, which serves as a comprehensive dataset for further analysis.

In addition to the above, the metrics from the csv file are used to train and fine-tune the Convolutional Neural Network (CNN) model and the Random Forest Classifier. Both of these models are then saved and used for future analysis.

One of the primary challenges was procuring the dataset, which required significant effort and resources to collect and organize. Additionally, obtaining high-quality data from scanned sheets was a significant challenge due to the need for people to write the sample texts in quiet environments without any hindrance.

Another challenge was understanding how to leverage code to capture the features from the text as advised by the graphologist. This required a deep understanding of the data extraction process and the ability to develop custom code to extract the required features from the text.

5. Conclusion and Future Enhancements

5.1 Conclusion

Slow learning disability detection in people helps to effectively treat them and also prevent low self-esteem. Few methods were applied to machine learning and deep learning techniques for predicting the probability of having slow learning disability. Existing methods have the limitations of lower efficiency in feature analysis and overfitting problems. By addressing the limitations of existing systems, this project offers a language-specific, accessible, and accurate solution for slow learning disability detection in Kannada.
In this project, the proposed CNN model shows 72% accuracy in predicting the slow learning disability and it has the advantage of effective feature analysis.
Random Forest classifier showed accuracy of 74%. Which needs the features extracted from the image data in the csv format.

5.2 Future Enhancements

Our research lays the groundwork for future advancements in dysgraphia diagnosis using machine learning. The future of dysgraphia diagnosis holds promise for greater accuracy and personalised support. One promising avenue is the exploration of multimodal datasets. This means incorporating not just written samples, but also data on factors like pressure applied while writing and pen lifts. These additional dimensions could provide a more comprehensive picture of writing difficulties.

Another exciting direction lies in developing novel methods to capture pressure and pen-lift data. This would allow for a more seamless and user-friendly data collection process.

Finally, researchers are delving deeper into the impact of writing systems (orthography) and specific tasks on machine learning models used for diagnosis. We can expect further studies to shed light on these aspects, leading to more robust and adaptable diagnostic tools. Additionally, with broader datasets encompassing various age groups, the technology could evolve to suggest targeted interventions for individuals with dysgraphia. This, coupled with more sophisticated models, could pave the way for not only diagnosing dysgraphia but also suggesting personalized intervention strategies.

6. References

[1] American Psychiatric Association (APA). (2013). Diagnostic and statistical manual of mental disorders (5th ed.). Author.

[2] Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., & Adam, H. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861.

[3] Lomurno, Eugenio, Linda Greta Dui, Madhurii Gatto, Matteo Bollettino, Matteo Matteucci, and Simona Ferrante. 2023. "Deep Learning and Procrustes Analysis for Early Dysgraphia Risk Detection with a Tablet Application" Life 13, no. 3: 598. https://doi.org/10.3390/life13030598

[4] Jayakanth Kunhoth, Somaya Al-Maadeed, Suchithra Kunhoth, Younus Akbari. (in press) 2022. “Automated Systems For Diagnosis of Dysgraphia in Children: A Survey and Novel Framework” https://doi.org/10.48550/arXiv.2206.13043

[5] Drotár, P., Dobeš, M. Dysgraphia detection through machine learning. Sci Rep 10, 21541 (2020). https://doi.org/10.1038/s41598-020-78611-9

[6] G. Dimauro, V. Bevilacqua, L. Colizzi and D. Di Pierro, "TestGraphia, a Software System for the Early Diagnosis of Dysgraphia," in IEEE Access, vol. 8, pp. 19564-19575, 2020, doi: 10.1109/ACCESS.2020.2968367.

[7] Yogarajah, P., & Bhushan, B. (in press). “Deep Learning Approach to Automated Detection of Dyslexia-Dysgraphia”. Paper presented at The 25th IEEE International Conference on Pattern Recognition, Milan, Italy. 2020.

[8] Ghouse, Fathima; Paranjothi, Kavitha; Vaithiyanathan, Revathi. 2022. “Dysgraphia Classification based on the Non-Discrimination Regularization in Rotational Region Convolutional Neural Network”. International Journal of Intelligent Engineering & Systems . 2022, Vol. 15 Issue 1, p55-63. 9p.

[9] Jayakanth Kunhoth, Somaya Al Maadeed, Moutaz Saleh, Younes Akbari. 2023. “CNN feature and classifier fusion on novel transformed image dataset for dysgraphia diagnosis in children”. Expert Systems with Applications. Volume 231. 120740. https://doi.org/10.1016/j.eswa.2023.120740.

[10] Nuriel Shalom Mor, Kathryn Dardeck. 2021. “Applying a Convolutional Neural Network to Screen for Specific Learning Disorder” Learning Disabilities: A Contemporary Journal 19(2), pp. 161-169.

[11] Avishka, I., Kumarawadu, K., Kudagama, A., Weerathunga, M., & Thelijjagoda, S. (2018). Mobile App to Support People with Dyslexia and Dysgraphia. 2018 IEEE International Conference on Information and Automation for Sustainability (ICIAfS). doi:10.1109/iciafs.2018.8913335

[12] Villegas-Ch, William, Isabel Urbina-Camacho, and Joselin García-Ortiz. 2023. "Detection of Abnormal Patterns in Children’s Handwriting by Using an Artificial-Intelligence-Based Method" Informatics 10, no. 2: 52. https://doi.org/10.3390/informatics10020052

[13] Iza Sazanita Isa, Wan Nurazwin Syazwani Rahimi, Siti Azura Ramlan, Siti Noraini Sulaiman. 2019. “Automated Detection of Dyslexia Symptom Based on Handwriting Image for Primary School Children” Procedia Computer Science, Volume 163, pp 440-449. https://doi.org/10.1016/j.procs.2019.12.127.

[14] V. Vilasini, B. Banu Rekha, V. Sandeep and V. Charan Venkatesh, "Deep Learning Techniques to Detect Learning Disabilities Among children using Handwriting," 2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICICT), Kannur, India, 2022, pp. 1710-1717, doi: 10.1109/ICICICT54557.2022.9917890.

[14] V. Vilasini, B. Banu Rekha, V. Sandeep and V. Charan Venkatesh, "Deep Learning Techniques to Detect Learning Disabilities Among children using Handwriting," 2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICICT), Kannur, India, 2022, pp. 1710-1717, doi: 10.1109/ICICICT54557.2022.9917890.

[15] N. N. Doshi, M. U. Maniyar, K. K. Shah, N. D. Sarda, M. Narvekar and D. Mukhopadhyay, "A Convolutional Recurrent Neural Network-Based Model For Handwritten Text Recognition To Predict Dysgraphia," 2023 International Conference on Intelligent Systems for Communication, IoT and Security (ICISCoIS), Coimbatore, India, 2023, pp. 145-150, doi: 10.1109/ICISCoIS56541.2023.10100514.

[16] Devi, G. Kavya. 2023. “Dysgraphia disorder forecasting and classification technique using intelligent deep learning approaches”. Progress in Neuro-Psychopharmacology and Biological Psychiatry. Volume 120. 110647. https://doi.org/10.1016/j.pnpbp.2022.110647.

[17] Overvelde, A., & Hulstijn, W. (2011). Handwriting development in grade 2 and grade 3 primary school children with normal, at risk, or dysgraphic characteristics. Research in Developmental Disabilities, 32(2), 540–548. doi:10.1016/j.ridd.2010.12.027

[18] C. Sharmila, N. Shanthi, S. Santhiya, E. Saran, K. Sri Rakesh and R. Sruthi, "An Automated System for the Early Detection of Dysgraphia using Deep Learning Algorithms," 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India, 2023, pp. 251-257, doi: 10.1109/ICSCDS56580.2023.10105022.

[19] Drotár, P., Dobeš, M. Dysgraphia detection through machine learning. Sci Rep 10, 21541 (2020). https://doi.org/10.1038/s41598-020-78611-9

[20] B.R. Kavitha and C. Srimathi, “Benchmarking on offline handwritten tamil character recognition using convolutional neural networks”, Jour- nal of King Saud University - Computer and Information Sciences, 34(4):1183–1190, 2022.

7. PO Attainment

BMS College of Engineering.
Department of Computer Science and Engineering.

Batch No.: B13 Date: 28-04-2024
Project Title: Detection of SLD in Kannada Vocabulary amongst Undergraduate students

PROGRAMME OUTCOMES	Level (1/2/3)	Justification if addressed
PO1	2	This research applies knowledge of engineering principles (pattern recognition, image processing, machine learning) to the complex problem of dysgraphia detection.
PO2	2	The project identifies and formulates the problem of dysgraphia detection, researches existing solutions, and analyzes data to reach substantiated conclusions.
PO3	2	A system for analyzing handwriting and classifying dysgraphia risk levels is designed, considering societal issues like affordability and language inclusivity.
PO4	2	Experiments are designed and conducted to collect handwriting data, with the data analyzed using various techniques and conclusions drawn based on the results.
PO5	2	Modern tools like open-source software and pre-trained models are employed for image processing and machine learning.
PO6	2	The project considers the societal impact of dysgraphia and the ethical implications of AI-based handwriting analysis.
PO7	1	While the project utilizes technology, the environmental impact is not directly addressed.
PO8	2	Ethical principles are followed in data collection and analysis, emphasizing anonymity and respect for participants.
PO9	3	Teamwork skills are demonstrated through coherent collaboration amongst everyone during the project
PO10	3	The project details and findings are communicated through the research paper and potentially presentations, showcasing communication skills.
PO11	2	Project management aspects like budget and timeline are explicitly mentioned.
PO12	3	This research contributes to a growing field and encourages further development in dysgraphia detection, demonstrating a commitment to lifelong learning.
PSO1	2	Software engineering principles are applied in developing the pre-processing and analysis algorithms for the system.
PSO2	2	The system analyzes visual data and processes it using algorithms, addressing aspects of network and mobile computational systems, although it is not a web-based application.
PSO3	3	Image processing and machine learning algorithms are utilized, showcasing the ability to design efficient algorithms.

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8. Details of list of publications related to this project

8.1 Research Paper

Automated Detection of Dysgraphia Symptoms In Primary and Middle School Children

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***Abstract*—Dysgraphia, a learning disability impacts handwriting fluency and legibility, which significantly hinder's a child's academic progress and self-esteem. The proposed work utilizes pattern recognition techniques, employing preprocessing techniques like Canny Edge Detection, WaterShed Segmentation and various image enhancement techniques to analyze written characters and extract relevant features using character-wise bounding boxes. This detailed analysis allows the system to capture subtle variations in letter formation and spacing that are often indicative of dysgraphia. Furthermore, A MobileNet architecture has been proposed to assess the system's performance and classify dysgraphia risk levels into three categories: Below Average(BA), Average(AV) and Above Average(AA). This categorization system provides valuable insights for educators and parents, enabling early intervention and tailored support for students struggling with dysgraphia. The model was trained using a data set of 940 images of handwriting samples from students studying in grades one to seven. Students were asked to write 20 words through dictation and another 20 words copied from the board. The proposed system aims to demonstrate immediate results, highlighting its potential for early detection and intervention.**

***Index Terms*—Deep Learning, Dysgraphia, Kannada Words, Learning Disability, MobileNet**

I. Introduction

Handwriting, though seemingly overshadowed by technological advancements, retains its significance in academics, communication, and self-expression. However, some children struggle with dysgraphia, making writing difficult. This learning disability affects 12-33% school-going children, impacting communication, self-expression, and idea capture [1]. Dysgraphia hinders academic performance, self-esteem, and future daily life. Early identification and support are crucial for children's development and well-being.

An intriguing age-related trend in learning disability prevalence is revealed in Figure 1. While rates remain below 2% for younger children, they culminate at 7% for ten-year-olds, highlighting a critical age for intervention [2].

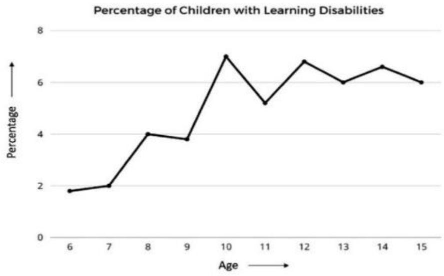

Fig. 1. Types of Dysgraphia

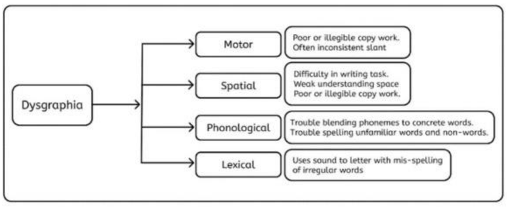

Fig. 2. Types of Dysgraphia

Fig 2. Shows the various kinds of dysgraphia observed in children and specifically this paper deals with motor and spatial dysgraphia.

Witnessing the struggles faced by young children with dysgraphia, particularly within the Kannada-speaking community, inspired us to undertake this research. Existing solutions are often time-consuming, expensive, and lack specific support for diverse languages and cultural backgrounds. By developing a novel, cost-effective, and user-friendly technology, we aim to make dysgraphia diagnosis and treatment more accessible and effective for all. The work aims to empower these children, remove barriers to learning, and unlock their full potential.

The paper is organized as follows: Section 2 provides a detail literature review on the work carried out in Dysgraphia and solution available. The data collection procedure and pre-processing is comprehended in Section 3 along with technical details on data extraction. Proposed Work and results are provided in Section 4. Conclusion and Future work are discussed in section 5.

II. Literature Review

A. Related Literature

Dysgraphia is a handwriting disorder and early detection of dysgraphia helps to treat the patient effectively. Few researches involve in the classification of dysgraphia using the devices like digitised writing tablets or iPads along with specialised styluses and proprietary apps to capture the handwriting. While these methods offer advantages, they fail to address the needs of Kannadiga communities.

In a study aiming to aid dysgraphia diagnosis, Dimauro et al. [3] developed TestGraphia software. This software utilises various document and feature selection algorithms to analyse children's handwriting (grades 2-5) and identify potential dysgraphia symptoms. Their experiments employed nine algorithms to extract and analyse text features, demonstrating improved dysgraphia detection accuracy and faster processing times compared to other methods. However, a few limitations were identified: borderline cases remained ambiguous due to inherent handwriting variances, and the impact of non- discriminatory letters (those not providing significant diagnostic information) was not addressed.

Yogarajah et al. [4] applied a Convolutional Neural Network (CNN) to automate the process of detecting dysgraphia as well as dyslexia amongst Hindi writing students. The model was trained on a dataset consisting of 164 handwritten hindi words from students with 'Strong Evidence of Risk' on DST-J from classes 1 to 5 and 103 from normal students. This method has incorporated Optical Character Recognition (OCR) on manually cropped images which still requires further processing such as skewing and cursive methods since OCR is not found to be stable. This study has reported an average accuracy of $(85.12 \pm 2.0)\%$. The lack of a large dataset as well as lack of phonic aspects hinder the study.

Ghouse, Paranjothi, and Vaithiyanathan [5] proposed a novel method called Non- Discrimination Regularization in Rotational Region Convolutional Neural Network (NDR-R2CNN). This model introduces balancing parameters in the loss function to achieve balanced class representation during training and eliminate irrelevant features to mitigate overfitting. This approach enables effective feature analysis and non-discriminatory word analysis. Their results demonstrate that NDR-R2CNN achieves an impressive accuracy of 98.2% , significantly outperforming the existing CNN model's 94.2% accuracy. However, one limitation noted is the lack of an attention layer, which could potentially further improve classification accuracy.

Kumoth et al. [6] explored various methods for dyslexia detection using deep convolutional neural networks (CNNs) and transfer learning. They employed several techniques, including fine-tuning pre-trained models like DenseNet201, feature extraction from CNNs, and ensemble learning with soft and hard voting strategies. These models were trained on separate datasets of word, pseudoword, difficult word, and sentence images. To evaluate their performance, the authors compared the CNNs to three traditional machine learning algorithms: SVM, AdaBoost, and Random Forest. Ultimately, the SVM model trained on word data achieved the highest accuracy of 91.7%.

However, the study's scalability is limited due to the dataset's focus on Slovak orthography. Proposed future research directions include developing new classifiers specifically trained on English data by leveraging the existing models for fine-tuning or initialization as well as exploring the potential of multimodal data (e.g., combining handwriting with acoustic features) which could further enhance dyslexia detection accuracy.

Mor et al. [7] adopted a transfer learning approach by utilising the pre-trained MobileNetV2 architecture for dyslexia detection. To adapt the model for dyslexia classification, the authors removed the final SoftMax layer designed for ImageNet's 1,000 classes and added three hidden layers of ReLU neurons. Despite promising results, their model's generalizability and robustness require further validation due to limited data diversity and size. Looking ahead, the authors have suggested exploring the assessment of handwriting across multiple languages from different populations to address these limitations and enhance the model's applicability.

While several studies like [8-12] have shown promise in dysgraphia detection using technology, their reliance on iPads, digitised tablets, and specialised styluses raises significant barriers to widespread adoption. These expensive devices, often paired with proprietary software, create an economic hurdle, particularly in developing countries or low-income communities. Dimauro et al.'s TestGraphia software, for instance, requires specific digitizers and proprietary apps, limiting its reach. Similarly, Ghouse et al.'s NDR-R2CNN model, while demonstrating high accuracy, relies on costly specialised hardware for data capture. This dependence on expensive technology not only restricts accessibility but also raises concerns about data privacy and software licensing costs. Furthermore, our use of open-source tools and methodologies ensures transparency and fosters further research and development tailored to specific languages like Kannada.

Despite the increasing prevalence of dysgraphia, particularly in developing countries like India, existing systems for its detection face significant limitations. Notably, most research and development efforts have focused on Western languages, with less focus on native language. This lack of attention leaves children from these communities vulnerable to undetected dysgraphia, hindering their academic and personal development.

Furthermore, existing systems often rely on expensive technologies like iPads [13] and digital tablets [14], with styluses [15] for handwriting analysis. This creates accessibility barriers for resource-constrained families and limits the scalability of such solutions. Additionally, these systems often use proprietary apps that are not publicly accessible. While some researchers have explored camera-based methods for dysgraphia detection, these approaches have not yet achieved the high accuracy levels which are often due to limitations in camera resolution, lighting conditions, and the ability to capture subtle handwriting details necessary for accurate analysis. making them unsuitable for classification.

III. Data Collection and Pre-Processing

The dataset was obtained from Jaigopal Garodia Rashtrotthana Vidyalaya, and created a specific Kannada language wordset and tested for students from grades one to seven. The dataset has two parts: first, students wrote 20 words by listening to the teacher (auditory), and second, they copied 20 words from the board (visual). The students filled grid boxes on A4 sheets in an organized way, making sure our data collection was consistent and systematic. This dataset, captures both how students hear and see words.

The teachers, who know the common mistakes students make while writing, provided the words. They also gave us a list of students who perform below average, average, and above average in the test. which then was used information to label the dataset as below average, average, and above average.

A. Preprocessing

To preprocess the dataset, we employed a systematic approach. The A4 sheets containing the dataset were scanned using a scanner. These sheets featured a grid-like structure with designated boxes, each housing words written by students. To isolate the relevant information, an OpenCV function was employed. This function adeptly cropped the scanned A4 sheet, focusing solely on the specific region containing the handwritten words within the designated box.

In the pre-processing phase, the input image underwent a sequence of techniques to enhance its suitability for subsequent analysis [16]. Initially, the image was converted to grayscale to simplify processing. Following this, a Gaussian blur was applied to mitigate noise and create a smoother representation. The image was then subjected to adaptive thresholding to segment it into foreground and background, facilitating the isolation of key features. To further refine the segmentation, an elevation map was generated using the Sobel operator, and a marker-based watershed segmentation [17] was employed. This approach allowed for the delineation of distinct regions within the image. Additionally, This multistep pre-processing pipeline aimed to optimize the image for subsequent dysgraphia symptom detection and comprehensive analysis.

Fig. 3. Preprocessed image

In Figure 3, you can see various filters applied to the image and different techniques used to get rid of any unwanted fuzziness. This helps in making the words clear and easy to recognize and detect.

B. Data Extraction

In our data extraction process, we thoroughly analyze segmented characters to pinpoint vital details for identifying dysgraphia symptoms in primary and middle school children. We concentrate on six crucial features for a robust statistical analysis: word length, word height, assessing overall character size; and character gap and height, revealing spacing and size relative to the baseline. We also consider "loss of interest" zones within characters and the skewed angle relative to the baseline for added insights.

To perform the statistical analysis, we use six specific features: word height and width, skewed angle of the written word and the height, width and distance between each character in the word. This selection is based on the simplicity of identification and analysis through handwriting scrutiny. We apply the Watershed algorithm to grayscale images with predefined markers, effectively extracting each character from the whole word. Watershed's adaptability to individual writing styles and character spacing variations makes it adept at handling touching or overlapping characters. The subsequent feature extraction involves drawing bounding boxes and contours [18] around each character, allowing the calculation of width, height, and skew angle. These extracted features are fundamental to our statistical analysis, enabling the automated detection of dysgraphia symptoms in primary and middle school children.

TABLE I
EXTRACTED FEATURES OF THE CHARACTERS

Character No	***Bounding box coordinates***	***width***	***height***	***gap***
1	(43, 25, 42, 77)	42	77	1
2	(86, 47, 64, 44)	64	44	1
3	(154, 50, 23, 33)	23	33	4
4	(190, 48, 68, 39)	68	39	13

Table-1 summarizes the features extracted from one of the 20 Kannada character in a student's handwritten word. Extracted features include bounding box coordinates, character width and height, and the gap between characters.

TABLE II
EXTRACTED FEATURES OF THE WORD

Word No	*word width*	*word height*	*skewed angle*
1	147	23	7.78495
2	140	20	0.84355
3	141	28	-3.19544
4	139	21	7.58495

Table-2 explains about the features extracted from four kannada words written by a student. The extracted features include width, height and the skewed angle of the word with respect to a reference line.

IV. Proposed Work and Results

To address the limitations of existing dysgraphia detection systems, the proposed work provides a novel approach specifically for Kannada handwriting. Unlike systems reliant on expensive tablets, our system will be accessible and affordable. We've also acquired Kannada-specific data from students of Jaigopal Garodia Rashtrotthana Vidyalaya in grades one to seven. These students wrote down both dictated and copied words on A4 sheets divided into grid boxes for consistent data capture.

Currently, pre-processing is carried out diligently on the dataset. This involves image cropping to extract relevant writing areas, denoising to remove unwanted artifacts, elevation to normalise contrast and brightness, and segmentation to isolate individual characters using both bounding boxes and contouring techniques. These steps ensure high-quality data for our model.

For analysis, a MobileNet architecture [19] is proposed, originally designed for mobile applications, that makes it suitable for resource-constrained environments. This model, trained on our pre-processed data, will predict a score for each writing sample. We'll then categorise these scores into three levels: Below Average, Average, and Above Average. This classification system provides a comprehensive assessment of handwriting fluency and legibility, making dysgraphia identification easier and more reliable.

A. Proposed Models

A MobileNet model will be used in this work for its noted effectiveness in detecting dysgraphia symptoms. This choice stems from our findings during the literature survey, where MobileNet stood out for its proficiency in conducting efficient feature analysis. Specifically designed for training machine learning models used in classification tasks, MobileNet appears to be a fitting option for our goal of identifying dysgraphia.

MobileNet is grounded in its capability to comprehend and learn patterns, which is crucial for accurately classifying dysgraphia symptoms in primary and middle school children. As an alternative model, we are also contemplating the inclusion of the Convolutional Neural Network (CNN) [20]. This decision is motivated by CNN's exceptional ability to identify features within images, providing a valuable benchmark for comparing the accuracy of both models. In essence, the prospective implementation of MobileNet and CNN aligns with our overarching objective of effectively training a model for precise dysgraphia symptom classification as our project continues to progress in its development stage.

B. Results

Fig 4. Illustrates a student's written word, wherein feature points are denoted in yellow, and the bounding box is in blue. Utilizing these points and the bounding box, features such as the inter-character gap, width, height, and skewed angle are computed.

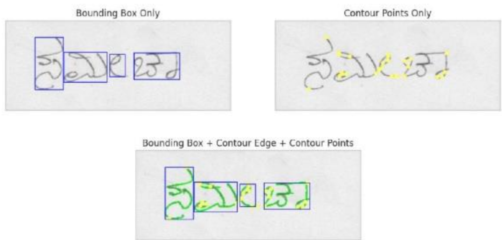

Fig. 4. Features extracted from the handwritten word

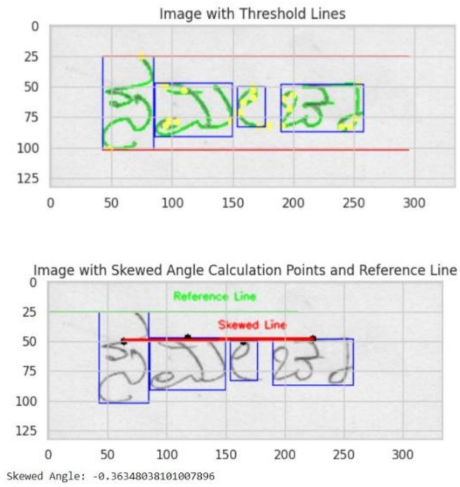

Fig. 5. Features extracted from the handwritten word

Fig 5. Illustrates the plotting of threshold lines denoted by red lines above and below the axis of the word, touching the highest feature point among all characters of the word. These individual topmost points of every character are denoted by black points and are utilized to determine the skew angle. The skew angle is determined either by fitting a line that touches the maximum of the points or through linear regression, which attempts to fit the line with the minimum distance from every point. The skew line is denoted by the red line.

Moving forward, our process advanced to the individual character level, where we successfully detected and extracted features such as each character's width, height, and the gap between each word. Additionally, our methodology extended to capture holistic characteristics of the entire word, including its length, height, and skew angle.

V. Conclusion

The work here encapsulates a comprehensive process, encompassing the entire trajectory from initial data collection and preprocessing to the establishment of a model tailored for the detection of dysgraphia symptoms in primary and middle school children. In the preliminary phases, rigorous efforts were devoted to the meticulous collection and preprocessing of data. Following this, the work adeptly applied contour drawing techniques, achieving successful character detection within the handwritten words. These accomplishments in character and word feature extraction lay a strong foundation for the subsequent phases of our research. By extracting key features, we've set the foundation for a robust model. These features, encompassing individual character traits and overall word characteristics, play a crucial role in defining our model's parameters. These results position us effectively for the upcoming training stage, highlighting the potential for an automated dysgraphia detection system with practical applications in education.

The future of this research lies in identifying more features that could reveal additional indicators of dysgraphia. Secondly, augmenting the dataset with specific words children find challenging could provide more targeted training data. Finally, shifting the focus from individual words to whole paragraphs represents the next step. Analyzing handwriting flow, sentence structure, and spatial arrangements within paragraphs help in understanding its impact on overall writing competency. This research can continue to evolve, offering more insightful and effective tools for early detection of dysgraphia.

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References

[1] Zvoncakova, Katarina and Mekyska, Jiri and Zvoncak, Vojtech, "Developmental dysgraphia a new approach to diagnosis", *International Journal of Assessment and Evaluation.* DOI:28.10.18848/2327-7920/CGP/v28i01/143-160, 2021.

[2] Dolly Mittal, Veena Yadav, and Anjana Sangwan. "Identification of dysgraphia: A comparative review", In Valentina E. Balas, G. R. Sinha, Basant Agarwal, Tarun Kumar Sharma, Pankaj Dadheech, and Mehul Mahrishi, editors, Emerging Technologies in Computer Engineering: Cognitive Computing and Intelligent IoT, pages 52–62, Cham, 2022. Springer International Publishing.

[3] G. Dimauro, V. Bevilacqua, L. Colizzi and D. Di Pierro, "TestGraphia, a software system for the early diagnosis of dysgraphia", *IEEE Access, vol. 8, pp. 19564-19575*, doi: 10.1109/ACCESS.2020.2968367, 2020.

[4] Yogarajah, P., Bhushan, B., "Deep learning approach to automated detection of dyslexia-dysgraphia", Paper presented at The 25th IEEE International Conference on Pattern Recognition, Milan, Italy, 2020., in press.

[5] Fathima Ghouse, Kavitha Paranjothi, Revathi Vaithiyanathan, "Dysgraphia classification based on the non-discrimination regularization in rotational region convolutional neural network", *International Journal of Intelligent Engineering and Systems, Vol. 15 Issue 1, p55-63. 9p*, 2022.

[6] Jayakanth Kunhoth, Somaya Al Maadeed, Moutaz Saleh, Younes Akbari, "CNN feature and classifier fusion on novel transformed image dataset for dysgraphia diagnosis in children", Expert Systems with Applications. Volume 231. 120740. https://doi.org/10.1016/j.eswa.2023.120740, 2023.

[7] Nuriel Shalom Mor, Kathryn Dardeck, "Applying a convolutional neural network to screen for specific learning disorder" Learning Disabilities: A Contemporary Journal 19(2), pp. 161-169, 2021.

[8] Iza Sazanita Isa, Wan Nurazwin Syazwani Rahimi, Siti Azura Ramlan, Siti Noraini Sulaiman. "Automated detection of dyslexia symptom based on handwriting image for primary school children" *Procedia Computer Science, Volume 163, pp 440-449.* https://doi.org/10.1016/j.procs.2019.12.127, 2019.

[9] V. Vilasini, B. Banu Rekha, V. Sandeep and V. Charan Venkatesh, "Deep learning techniques to detect learning disabilities among children using handwriting", *2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICICT), Kannur, India, pp. 1710-1717*, doi: 10.1109/ICICICT54557.2022.9917890, 2022.

[10] N. N. Doshi, M. U. Maniyar, K. K. Shah, N. D. Sarda, M. Narvekar and D. Mukhopadhyay, "A convolutional recurrent neural network-based model for handwritten text recognition to predict dysgraphia", International Conference on Intelligent Systems for Communication, IoT and Security (ICISCoIS), Coimbatore, India, 2023, pp. 145-150, doi: 10.1109/ICISCoIS56541.2023.10100514, 2023.

[11] Isuru Avishka, Kalana Kumarawadu, Akalanka Kudagama Mihiran Weerathunga, Samantha Thelijjagoda. "Mobile app to support people with dyslexia and dysgraphia", *IEEE International Conference on Information and Automation for Sustainability (ICIAfS).* doi:10.1109/iciafs.2018.8913335, 2018.

[12] Villegas-Ch, William, Isabel Urbina-Camacho, and Joselin García-Ortiz. "Detection of abnormal patterns in children's handwriting by using an artificial-intelligence-based method" Informatics 10, no. 2: 52. https://doi.org/10.3390/informatics10020052, 2023.

[13] Eugenio Lomurno, Linda Greta Dui, Madhurii Gatto, Matteo Bollettino, Matteo Matteucci, and Simona Ferrante, "Deep learning and Procrustes analysis for early dysgraphia risk detection with a tablet application", *Life 13, no. 3: 598.* https://doi.org/10.3390/life13030598, 2023.

[14] Jayakanth Kunhoth, Somaya Al-Maadeed, Suchithra Kunhoth, Younus Akbari, "Automated systems for diagnosis of dysgraphia in children: a survey and novel framework", https://doi.org/10.48550/arXiv.2206.13043, 2022

[15] P. Drotár, M. Dobeš, "Dysgraphia detection through machine learning", *Sci Rep 10, 21541*, https://doi.org/10.1038/s41598-020-78611-9, 2020.

[16] A. Overvelde, W. Hulstijn, "Handwriting development in grade 2 and grade 3 primary school children with normal, at risk, or dysgraphic characteristics", Research in Developmental Disabilities, 32(2), 540–548. doi:10.1016/j.ridd.2010.12.027, 2011.

[17] C. Sharmila, N. Shanthi, S. Santhiya, E. Saran, K. Sri Rakesh and R. Sruthi, "An automated system for the early detection of dysgraphia using deep learning algorithms", 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India, pp. 251-257, doi: 10.1109/ICSCDS56580.2023.10105022, 2023.

[18] Devi, G. Kavya, "Dysgraphia disorder forecasting and classification technique using intelligent deep learning approaches". Progress in Neuro-Psychopharmacology and Biological Psychiatry. Volume 120. 110647. https://doi.org/10.1016/j.pnpbp.2022.110647, 2023.

[19] Zaidah Ibrahim, Norizan Mat Diah, Muhammad Eirfan Azmi, Azizi Abdullah, and Nor Azan Mat Zin, "Real-time mobile application for handwritten digit recognition using mobilenet", Proceedings of the 11th International Conference on Robotics, Vision, Signal Processing and Power Applications, pages 1003–1008, Singapore, 2022. Springer Singapore.

[20] B.R. Kavitha and C. Srimathi, "Benchmarking on offline handwritten tamil character recognition using convolutional neural networks", Journal of King Saud University - Computer and Information Sciences, 34(4):1183–1190, 2022.

8.2 Publications

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