Dissertation on

"Multi Modal Handwriting Analysis using Machine Learning "

Submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology
in
Computer Science & Engineering

UE22CS320A – Capstone Project Phase - 1

Submitted by:

Naman Jain	**PES1UG22CS371**
Shreeya Guggari	**PES1UG22CS569**
Riya Shetty	**PES1UG22CS481**
Prakul Nayak	**PES1UG22CS371**

Under the guidance of

Dr. Priyanka H
Associate professor
PES University

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
FACULTY OF ENGINEERING
PES UNIVERSITY
(Established under Karnataka Act No. 16 of 2013)
100 feet Ring road, BSK 3rd stage, Hosakerehalli, Bengaluru – 560085

PES UNIVERSITY

(Established under Karnataka Act No. 16 of 2013)
100ft Ring Road, Bengaluru – 560 085, Karnataka, India

FACULTY OF ENGINEERING

CERTIFICATE

This is to certify that the dissertation entitled

“Multi Modal Handwriting Analysis using Machine Learning "

is a bonafide work carried out by

Naman Jain	**PES1UG22CS371**
Shreeya Guggari	**PES1UG22CS569**
Riya Shetty	**PES1UG22CS481**
Prakul Nayak	**PES1UG22CS428**

In partial fulfillment for the completion of Fifth-semester Capstone Project Phase - 1 (UE22CS320A) in the Program of Study -Bachelor of Technology in Computer Science and Engineering under rules and regulations of PES University, Bengaluru during the period Aug. 2024 – Dec. 2024. It is certified that all corrections/suggestions indicated for internal assessment have been incorporated in the report. The dissertation has been approved as it satisfies the 5th-semester academic requirements in respect of project work.

Signature	Signature	Signature
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Associate Professor	Chairperson	Dean of Faculty

External Viva

Name of the Examiners	**Signature with Date**
1. ____________________	____________________
2. ____________________	____________________

DECLARATION

We hereby declare that the Capstone Project Phase - 1 entitled **"Multi Modal Handwriting Analysis using Machine Learning"** has been carried out by us under the guidance of **Dr. Priyanka H, Associate Professor** and submitted in partial fulfillment of the course requirements for the award of the degree of **Bachelor of Technology** in **Computer Science and Engineering** of **PES University, Bengaluru** during the academic semester Aug – Dec 2024. The matter embodied in this report has not been submitted to any other university or institution for the award of any degree.

Naman Jain	**PES1UG22CS371**	________________
Shreeya Guggari	**PES1UG22CS569**	________________
Riya Shetty	**PES1UG22CS481**	________________
Prakul Nayak	**PES1UG22CS428**	________________

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1. PROBLEM STATEMENT

Handwriting is more than a means of communication; it reflects identity, behaviour, and cognitive abilities. However much of the hidden information goes unnoticed due to limitations in traditional methods of analysis.

A particular key challenge involves signature authentication, in that verification procedures are manually conducted, with possible human errors, especially over highly sensitive areas such as those including banking and legal documentation. By the same token, various styles of handwriting go to make it really challenging to accurately interpret; it sometimes gets messy or inconsistent while handwriting recognition and digitization is being carried out.

Other usually unrecognized areas are those of dysgraphia detection, which is a type of learning disability related to writing skills. Because these are not properly standardized tools, dysgraphia more than often goes undetected into the lives of children and adults at the time of living and educational phases.

This project aims at overcoming some of these challenges with a multi-modal machine learning approach for better accuracy and efficiency in signature authentication, digitization of handwriting, and dysgraphia detection. The work is expected to make handwriting analysis more practical and impactful with scalable and reliable solutions.

2. SCOPE

This project is focused on the possible exploration of multimodal handwriting analysis using machine learning techniques. The key objective of this work is to develop a system for handwriting analysis that would support achieving the following three important objectives:

Signature Authentication :
Verification of the authenticity of signatures for applications in banking, legal, and identity verification systems. This includes forging, variation in signature styles, and enhancement of the accuracy of verification.

Handwriting Recognition and Digitization :
Having an automated system translate handwritten papers onto machine-readable formats, even amidst variation in style, size, and quality. The system represents document digitization processes that heighten efficiency in data collection for record-keeping.

Dysgraphia Detection :
Dysgraphia is a type of learning disability that affects one's writing ability. This will in turn help the teachers, parents, and medical professionals plan for timely interventions. The focus here is to determine special patterns in handwriting that signal this condition. The project scope further involves the development of scalable, efficient, and adaptive models that can be applied in real life, ensuring that they are applicable across diverse languages and handwriting styles.

3. FEASIBILITY STUDY

- Technical Feasibility

  With the general development of machine learning and, even more so, computervision and natural language processing, it was highly possible to develop certain systems for handwriting analysis. Tools such as CNN and OCR can be reused andadapted for the task. The availability of datasets of handwritings, in combination with tools like TensorFlow or PyTorch, increases the feasibility of such a project.

- Operational Feasibility

  The project will have practical applications in industries like banking, education,and healthcare. In addition, signature authentication systems will simplify processes of verification, handwriting recognition will improve document digitization, and dysgraphia detection will help foster early diagnosis and support.

- Economic Feasibility

  Although machine learning will involve some investment in machinery and datacollection initially, all the long-term benefits make sure the cost is well justified. Using any open-source library and even pre-trained models can reduce the time of development, thereby yielding cost-effectiveness. Financially, its application across high-demand fields, further into education and security itself, ensures its financial credibility. Social Feasibility This project deals with very social issues: fraud prevention concerning signature verification and help for kids and adults with learning disabilities. Due to its scalability, it does have big potential to impact manifold areas in a very positive sense and, therefore, improve the accessibility to handwriting analytical tools greatly.

4. LITERATURE SURVEY

4.1 Dysgraphia-1

Authors - N. N. Doshi, M. U. Maniyar, K. K. Shah, N. D. Sarda, M. Narvekar and D. Mukhopadhyay

Modules Used

- Convolutional Neural Network (CNN): It helps extract features of handwriting such as shape and pattern.
- Recurrent Neural Network: Processes sequential handwriting data for better prediction of text.
- OCR (Optical Character Recognition): the transformation of images of handwriting into text for further analysis.

Pros

- ✓ Fully automated, thus efficient in carrying out dysgraphia detection with less dependence on manual tests.
- ✓ Detailed Analysis: Provides specific mistake types such as substitutions, omissions, reversals, and risk prediction metrics.
- ✓ Child-Friendly Interface: Ensures a less intimidating testing environment.

Cons

- Dataset Limitation: The IAM dataset is designed to be focused on English, thereby limiting multilingual applications.
- Variability in Handwriting: The accuracy depends on the inconsistent style of handwriting that may lead to misclassification.
- Threshold Sensitivity: Fixed error threshold may not generalize to all cases.

Gaps in Research

Dataset Diversity: There are no multilingual datasets; moreover, variability in the samples of handwriting limits model training.

Limitation of Language Generalization: The system is limited to English, excluding populations that do not understand English.

Broader Disabilities: The study is focused on dysgraphia, excluding co-occurring conditions such as dyslexia or dyscalculia.

Conclusion

The proposed system represents a promising step toward the automation of dysgraphia detection, thus offering effective and detailed insights for early intervention. However, the expansion of the dataset to include diverse languages, integrating more learning disorders, and addressing handwriting variability will enhance the effectiveness and global applicability of the system.

4.2 Dysgraphia-2

Authors - J. Mekyska, M. Faundez-Zanuy, Z. Mzourek, Z. Galaz, Z. Smekal and S. Rosenblum

Modules Used

- Sequential Writing Acquisition: Digitizing tablet to capture the data about handwriting.
- Feature Extraction: Complex parameterization in order to quantify kinematic aspects, geometry, fluency, in-air movement, and other characteristics of handwriting.
- Intrawriter Normalization: Simple subtraction method for feature normalization.
- Dysgraphia Rating: Random Forest Classifier and Classification and Regression Trees for Dysgraphia Discrimination and HPSQ total score estimation.

Pros

- ✓ High Accuracy: Dysgraphia discrimination showed high sensitivity and specificity, reaching 96% each.

  The research proposed a method for automatic diagnosis and estimating the difficulty level.
- ✓ Complex Parameterization: Features used in the analysis ranged from simple to complex; kinematic, nonlinear dynamic, and other measures were also utilized.
- ✓ Intrawriter Normalization: Improved discrimination and HPSQ estimation accuracies.

Cons

- Limited Dataset: The dataset used was rather small, involving 54 participants.
- Limitation of In-Air Movement: The digitizer will not capture in-air movements exceeding a height of 1 cm from the surface.
- HPSQ subjectivity: The HPSQ is scored subjectively by the clinician, and the results can be variable.

Gaps in Research

- Larger Dataset Validation: This requires further validation on a larger and more varied dataset.
- In-Air Movement Accuracy Improvement in the capture of a user's in-air movements is expected to augment the system's accuracy rating.
- Inter-Rater Reliability: Furthermore, the subjective nature of the ratings provided in the HPSQ requires multiple clinician ratings that have been compared to the automated system. Conclusion: This work presents an automated system for developmental dysgraphia identification and rating by handwriting analysis. It reached very high accuracy for dysgraphia discrimination and high for HPSQ total score estimation. However, its performance needs to be further validated with more extensive datasets. Moreover, capturing in-air movement data is at a rudimentary level and should be improved. The subjectivity of the ratings included in the HPSQ can also be taken further in order to provide more reliable output of the system.

4.3 Dysgraphia-3

Authors - Dankovičová, J. Hurtuk and P. Feciľak

Modules Used

o Random Forest

o Support Vector Machine - SVM

o Adaptive Boosting (AdaBoost)

o Principal Components Analysis - PCA

Pros

- ✓ Holistic approach: this paper gives a full description of the approach one can take for attribute extraction, classification, and even visualization in dysgraphia detection.
- ✓ Multi-Class Classification Techniques: The proposed system uses a few machine learning techniques, namely Random Forest, SVM, and AdaBoost, integrated in one to predict dysgraphia with a better classification rate.
- ✓ Visualization: Allowing the use of PCA for attribute visualization helps in the understanding of the structure of data and the realization of patterns.
- ✓ Objective Evaluation: The test is aimed at giving as objective an evaluation as possible from the handwriting samples, thereby unifying the results by minimizing variability among specialists.
- ✓ Detailed Implementation: The paper is very clear in explaining how the implementation was done, from data collection to attribute extraction and classification steps.

Cons

- Limited sample size: The total number of handwriting samples included in this study is just 78, which may be rather not indicative.
- Age Group Focus: The research has put its focus on subjects aged between 10-13 years, which may not be that useful in applications on any other age group.
- There is some overlapping of the attributes. Some of the attributes repeat; hence, not all attributes are a reflection of the impairment in handwriting.
- Objective evaluation: The proposal is to undertake an objective evaluation system; however, elaborations lacking on how that would be done in real life. Research Gaps Expanded Sample Size: This system needs to be trained and tested on more diverse and larger datasets to achieve better generalization.
- Expanding of the Age Group: The system is required to be expanded with other age groups in order to make it more applicable.
- Feature Selection: Identifying and selecting the features showing the best reflection of this problem of handwriting impairment requires a more in-depth study in the future.
- Objective Evaluation Implementation: The study needs to provide more details on how the objective evaluation system would be implemented in practice.
- User feedback: The system needs to be more accurate and with more ease of usability by way of user feedback.

Conclusion

The approach reported within this paper is a broad one: it detects dysgraphia with the use of different machine learning methods like Random Forest, SVM, and AdaBoost. This system recognizes features from the samples for the process of dysgraphia detection through handwriting. The application of various forms of classification dramatically improves accuracy in dysgraphia detection. In the proposed system, the attribute visualization will be done by PCA such that the structure and pattern of the data may be understood. Future work will increase the sample size and involve other age groups, select the attributes carefully, and explain the implementation details about how to carry out objective evaluation. Applications might range from education and health to the development of assistive technologies for people affected with dysgraphia.

4.4 Signature Authentication-1

Authors - V. Hindumathi, J. Chalichemala, E. Ameya, V. Kavya Sri and B. Vaibhavi

Modules Used

- MATLAB: This software tool should be used for implementing the whole pre-processing, feature extraction, and classification stages that are part of the system for signature verification.
- Negative Selection Algorithm (NSA): Feature extraction was done for the signature images, mainly used for anomaly detection and classification.
- AspectRatio: Height-to-width ratio calculation used to establish the signature image's proportion.
- Maximum Horizontal and Vertical Projection: Techniques that give insight into the distribution of black pixels in the signature image.
- Centroid Computation: Calculation of the center of mass will provide the centroid of the signature image horizontally and vertically.
- Slope Curve Analysis: The study of the font and strokes in the signature.

Pros

- ✓ Efficiency: It is time- and energy-saving as compared to the general manual methods of signature verification.
- ✓ Reduced fraud risks since the automated systems cut on fraudulent authentication.
- ✓ Minimized Human Error: The system reduces human error in the verification of signatures.
- ✓ Scalability: The dataset used is from 15 individuals, and scalability depends on the capability of the system.

Cons

- Complexity in Feature Extraction: Feature extraction itself, such as slope curve and center of mass, is complex and may be in need of even sophisticated algorithms.
- The quality of the images fed into the system may be compromised by noise and other artifacts, on which the success of this system depends.
- Threshold Sensitivity: The system is sensitive to the value of the threshold error used for classification and may be subject to further tuning depending on the dataset.

Gaps in Research

- Dynamic Feature Incorporation: Dynamic features include pen pressure, speed, and so on. Dynamic features may give more accuracy to the proposed system; the paper generally focuses on static features only.
- Real-World Application Challenges: No elaborate discussion regarding performance in real-world use cases, where smudging or partial obscuring of signatures may occur. Generalization Across Datasets: The authors do not investigate the potential of the system to generalize across different datasets or populations, which is very relevant in real-world applications.

Conclusion

The proposed offline handwritten signature verification system using image processing techniques gives promising results for the separation of genuine and forged signatures. However, its performance is totally dependent on the strength of feature extraction methods and proper threshold settings. Dynamic features should be integrated with the current system and the performance should be further tested in different scenarios for real-world applicability and reliability.

4.5 Signature Authentication-2

Authors - J. Ramod, P. Shrivastav, R. Shetty, V. Nimbalkar and L. Ragha

Modules Used

- Siamese Network for one-shot learning: to compare and verify the authenticity of signatures.
- Image Preprocessing: Grayscaling, Scaling, Thresholding.
- Feature Extraction: Characteristics of stroke-pressure, speed.
- Distance Calculation for similarity score between signatures.
- Verification to classify the signatures into genuine or forged.

Pros

- ✓ High degree of precision in distinguishing between genuine and forged signatures.
- ✓ It also allows one-shot learning and enables efficient signature verification.
- ✓ Robust to signature variations regarding speed, pressure, and stroke shape.
- ✓ Enhances security by detecting forged signatures

Cons

- Computationally intensive during model training.
- Performance depends upon the quality and quantity of the data.
- It is mostly applied to a dynamic signature that is online but not a static one that is offline

Gaps in Existing Research

- ➢ Real Time Implementation Challenges.
- ➢ Integration, if required, with other biometric systems.
- ➢ Detection of sophisticated forgeries was also enhanced.
- ➢ The Siamese Network-based signature verification system proposed here ensures much higher accuracy, security, and adaptiveness than traditional systems. Though it also carries many challenges regarding false positives

and computational complexity, the presented approach comes out among one of the strongest that can be used for verification of handwritten signatures in security-critical applications. Scalability and multi-modal authentication are other interesting features to be emphasized here.

4.5 Handwriting Text Recognition-1

Authors - Z. Noubigh and M. Kherallah

Modules Used

- Trajectory Recovery Methods
- Temporal order recovery from static handwriting images by re-establishing the pen stroke sequence.
- It combines the local approaches, such as ambiguous zone detection, with global approaches including optimal path reconstruction.
- Graph-based representations:
- Creates a skeleton graph of the handwritten images for stroke sequence detection using graph traversal algorithms, specifically Euler path detection.
- Image preprocessing: binarization, contour extraction, skeletonization enhance image quality to extract major features of handwriting.

Pros

- ✓ Improved offline recognition: It enhances the performance of static handwriting recognition with the help of dynamic features from trajectory recovery.
- ✓ Versatility: Applied to various scripts, from Latin and Chinese to Arabic and styles of writing such as mathematics.
- ✓ Dynamic Feature Extraction: It extracts critical features, such as stroke direction and sequence, thus improving the accuracy.

Cons

- Ambiguity Challenges: Ambiguous zones refer to those areas where intersection or overlapping strokes occur, reducing the accuracy and making the recovery of the trajectory more difficult.

- Dependence on Previous Knowledge: The strategy usually is effective only upon assumptions made about the direction and styles of script and writing, thus making minimal adaptability.
- Complexity in multi-stroke characters: Recovery in multi-stroke systems is more computationally expensive and involves more robust algorithms.

Research Gaps

Ambiguous Zone Analysis: The ambiguity resolution with the existing approaches at the junction of strokes needs further refinement for improved performance.

Diversity of the Dataset: Most of the studies have located their work within certain scripts like Arabic or Latin; these thus need an extension into the varied systems of writing.

Integrations into Real-Time Systems: It also could not be applied in practical fields due to its high computational overhead, which requires real-time handwriting recognition or an online application.

Conclusion

Trajectory recovery closes the gap between offline and online handwriting recognition, giving a serious boost to static recognition by adding dynamic features. However, there are two major challenges: removing ambiguities and the extension of this approach for more scripts and real applications in real time.

4.6 Handwriting Text Recognition-2

Authors - K. Saini, K. Sharma, A. Agarwal, K. Jayan and D. Dev

Modules Used

- CNN: used for feature extraction and classification of handwritten texts.
- RNN: To model the sequence of written text.
- LSTM - Long Short-Term Memory: It models long-range dependencies, one of the main features of handwriting.
- Gated CNN and GRU: It may provide better performance and would not suffer from vanishing gradient problems.
- Seq2Seq Model: This is a mix of CNN/RNN towards improving performance in handwriting recognition.
- CCTC : Connectionist Temporal Classification. The time series of recognitions tasks are aligned to this model.

Pros

- ✓ High Accuracy: Through deep learning, hand written objects are recognized much more effectively.
- ✓ Flexibility: It deals with everything kind of handwriting in hand-written or printed form.
- ✓ Language particular models: The system intended to enhance the recognition results for Russian and Kazakh, among others.
- ✓ Scalable: handles large datasets of complicated tasks of handwriting.

Cons

- Difficulty: Most deep learning models are very computationally expensive.
- Data-dependent: Highly dependent on the quality and amount of training data\
- False Positives/Negatives: Still errors might occur, in particular because of unclear handwritings.

Gaps in the Research

- Multilingual Support: Increasing demand for more advanced models that can work in multiple languages.
- Offline Recognition: It recognizes within the scanned document.
- Complex Format Document Handling: Handwritten recognition is very difficult with complex format documents.
- Model Robustness: This model is still not close to the performance it has been shown on degraded or noisy text.

Conclusion

It is very true that architecture, based on deep learning techniques for the recognition of handwritten text using CNN, RNN, and LSTM, has considerably made it effective, accurate, and adaptive. However, it lacks multilingual support and proper complex handling of handwriting. Discussion in the future course should continue with increasing model robustness, decreasing data dependency, and improving recognition results offline

4.7 Handwriting Text Recognition-3

Authors - S. MS, S. G and A. D. R

Modules Used

- Convolutional Neural Network
- Recurrent Neural Network
- Long Short-Term Memory (LSTM)
- Regional-Based Convolutional Neural Network Model (RCNN)

Pros

- ✓ Comprehensive Approach: It discusses everything about handwritten text recognition in the paper from model building to the digitization of texts.
- ✓ Use of Deep Learning: Deep learning algorithms are adopted by the system, while state-of-the-art image and sequence recognition tasks will be handled or analyzed by CNN, RNN, LSTM, and RCNN.
- ✓ Spell Check Integration: The system also integrates a spell check module to minimize errors in text conversion, hence increasing the overall accuracy of the recognition process.
- ✓ User-Friendly Interface: Using Flask to create a web application provides ease of access and a friendly interface for the system.
- ✓ Detailed Implementation: The implementation is clearly explained in the paper, from data collection and model training to the steps of text recognition.

Cons

- Limited Dataset: IAM, MNIST, and special character datasets are mainly used in
- this research work, which may not cover all the variation in handwriting.
- While the paper spells out the need to equip with a spell-check module in order to lessen mistakes, it does not further present the implementation in details, nor the results of this.
- Generalization: No discussion is made about the performance of the system for different languages or scripts of handwritten texts. The paper does not discuss the

efficiency of such a system for real time or near-real time cases of handwritten text recognition.

Gaps in Research

- Generalization: The system needs to be trained and tested with more variety on a larger dataset.
- The spell check module needs further development and testing for efficiency in reducing errors.
- Language and Script Support: The system should be extended to support multiple languages and scripts to increase its applicability.
- Real-Time Process: The system must utilize real-time or near real-time processing in order for it to become feasible during applications requiring instant recognitions. UserFeedback: There may be a need to provide mechanisms for user feedback. This would help in further enhancement of the system's accuracy and its usability.

Conclusion

This paper therefore adopted a comprehensive approach in presenting the state of the arts in the use of some deep learning models, such as CNN, RNN, LSTM, and RCNN in recognizing handwritten texts of documents and notes. Each handwritten text is transformed with this system into digital words. Deep learning algorithms have improved upon the accuracy and efficiency at which handwritten character recognition would have been traditionally done by increasing their speed. A spell-check module is employed to reduce the errors in converting text. This, in turn, increases the overall accuracy of the recognition process.

4.9 Handwriting Text Recognition-4

Authors - R. Vaidya, D. Trivedi, S. Satra and P. M. Pimpale

Modules Used

- Convolutional Neural Network, CNN
- TensorFlow

Pros

- ✓ Original Approach: The paper focuses on the offline handwritten character recognition methodology using deep neural networks-a great milestone in this regard.
- ✓ Full-featured system: the system consists of an Android application, which provides interaction to the user, and a server, which processes this information. The system is user-friendly and accessible.
- ✓ High Accuracy: The model achieves an accuracy of up to 94%, which is commensurate with a performance for handwritten character recognition.
- ✓ Use of State-of-the-Art Tools: The paper employs modern tools and libraries suchas TensorFlow, Python, OpenCV, and Android to ensure that the system is basedon robust and updated technologies.
- ✓ Detailed Implementation: The paper gives minute details on implementation fromimage processing to neural network training, which is useful for others to replicatethe work.

Cons

- Limited Language Support: This system currently supports only the Englishlanguage, hence limiting the scope of its application on other languages.
- No Error Correction: It does not include mechanisms for error correction thatwould enhance the accuracy of recognized text.

- Real-time Processing: The efficiency of the system in real or near-real time forrecognizing handwritten texts is not discussed, which is critical in many applications. Special Symbols: The system does not recognize special symbols, which limits its use in certain applications.

- Cursive Recognition: The system can support cursive handwriting, but with further improvements in accuracy and wider support for more complex cursive styles.

Research Gaps

- Language expansion: The system should be expanded to handle multiple languages to increase its potential usefulness.
- Mechanisms for Error Correction: It would be much easier if error correction mechanisms had been integrated into the prototype; accuracy in the recognized text could improve significantly.
- Real-Time Processing: The system should be optimized to allow for real-time or near-real-time processing, making it suitable for applications requiring immediate recognition.
- Special Symbols Recognition: The addition of special symbols will enhance the system's applicability in various fields. Future research and development in cursive handwriting should focus on improving recognition of such writings.

Conclusion

This paper proposes a very novel approach for offline handwriting character recognition using deep neural networks. The proposed system will integrate CNN, TensorFlow, in the development of one comprehensive solutionto recognize a handwritten text. The system demonstrates an accuracy of up to 94%, including an android application for user interaction and containing a server for processing the same. Future work can be done on increasing language support, improving cursive recognitions, adding special symbol supports, optimizing for real- time processing, and allowing mechanisms of errorcorrection.

CONCLUSION

The given project, which uses advanced machine learning for improving handwriting and verification of signatures, yields much better performance with less data. This is scalable, objective, and generalizes well for users. While there do exist challenges in this regard, such as dataset variability, the approach does enhance the verification systems much better, with a very promising insight into real-world use.

PROJECT PLAN FOR CAPSTONE – PHASE 2

We are going to be looking for a larger dataset than what we currently have for our project as well as selecting and testing out the right machine learning algorithms to train our dataset.

REFERENCES

1. V. Hindumathi, J. Chalichemala, E. Ameya, V. Kavya Sri and B. Vaibhavi, "Offline Handwritten Signature Verification using Image Processing Techniques," 2023 IEEE 8th International Conference for Convergence in Technology (I2CT).

2. J. Ramod, P. Shrivastav, R. Shetty, V. Nimbalkar and L. Ragha, "Signature Authentication Verification using Siamese Network," 2023 6th International Conference on Advances in Science and Technology (ICAST).

3. K. Saini, K. Sharma, A. Agarwal, K. Jayan and D. Dev, "Handwritten Text Recognition Using Machine Learning," 2023 International Conference on Sustainable Emerging Innovations in Engineering and Technology (ICSEIET).

4.Z. Dankovičová, J. Hurtuk and P. Feciľak, "Evaluation of Digitalized Handwriting for Dysgraphia Detection Using Random Forest Classification Method," 2019 IEEE 17th International Symposium on Intelligent Systems and Informatics (SISY), Subotica, Serbia, 2019.

5. 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).

6. S. MS, S. G and A. D. R, "Handwritten Text Recognition Using Machine Learning and Deep Learning," 2023 Eighth International Conference on Science Technology Engineering and Mathematics (ICONSTEM).

7. R. Vaidya, D. Trivedi, S. Satra and P. M. Pimpale, "Handwritten Character Recognition Using Deep-Learning," 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT).

8. Z. Noubigh and M. Kherallah, "A survey on handwriting recognition based on the trajectory recovery technique," 2017 1st International Workshop on Arabic Script Analysis and Recognition (ASAR), Nancy, France, 2017.

10. J. Mekyska, M. Faundez-Zanuy, Z. Mzourek, Z. Galaz, Z. Smekal and S. Rosenblum, "Identification and Rating of Developmental Dysgraphia by Handwriting Analysis," in IEEE Transactions on Human-Machine Systems.

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