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Yibin Peng *

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Machine Learning Methods for Handwriting Recognition

Yibin Peng

1 School of Physics and Information Engineering, Jiangsu Second Normal University, Nanjing, Jiangsu 210016, P R China
Email: YP (2327755933@qq.com)

Abstract: Machine learning is a fundamental aspect of artificial intelligence that involves the development of algorithms and models that allow computers to learn and make predictions or decisions without explicit programming. With the development of neural networks, back-propagation algorithms and deep learning, machine learning has made breakthroughs in the fields of image recognition, natural language processing and handwriting recognition using machine learning techniques. The advent of deep learning has revolutionized the field of handwriting recognition, using convolutional neural networks, recurrent neural networks, and sequence-to-sequence models to provide solutions that go beyond machine learning methods and significantly improve the accuracy and robustness of handwriting recognition systems. But challenges remain, including the need for large labelled datasets, computational resources and addressing potential biases. As research in deep learning techniques continues to drive handwriting recognition closer towards realisability, machine learning approaches remain at the forefront.

Keywords: Handwriting recognition; Machine learning (ML); Deep learning; Transfer learning strategy; Handwritten datasets

1. Introduction

Handwriting recognition [1], also known as Handwritten Text Recognition (HTR) or Optical Character Recognition (OCR) for handwritten documents, is a field within image analysis that focuses on the conversion of handwritten text into machine-readable and editable text. This technology plays a crucial role in digitizing historical documents, personal notes, and other handwritten materials that may be challenging for traditional OCR systems designed for printed text. Handwriting recognition systems employ advanced algorithms and machine learning models to analyze the shapes, strokes, and patterns in handwritten characters, enabling the extraction of meaningful textual content.

One of the primary challenges in handwriting recognition lies in the inherent variability of individual handwriting styles. People exhibit diverse writing habits, making it necessary for recognition systems to adapt and learn from various writing samples. Modern handwriting recognition systems often leverage deep learning techniques, such as convolutional neural networks (CNNs) [2, 3] and recurrent neural networks (RNNs), to capture complex spatial and temporal dependencies within handwritten text. Training these models on large datasets with diverse handwriting styles helps improve accuracy and generalization.

The applications of handwriting recognition are multifaceted. Beyond the digitization of historical documents, it finds utility in forms processing, where handwritten information on paper forms is automatically extracted and processed. In educational settings, handwriting recognition aids in grading handwritten exams and assessments. Additionally, it enhances the user experience in digital devices by enabling handwritten input on touchscreens and stylus-equipped devices. As technology continues to advance, handwriting recognition systems are becoming more sophisticated, contributing to the seamless integration of handwritten content into the digital landscape.

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2. Background of Machine Learning

Machine learning (ML) [4, 5] forms a foundational aspect of artificial intelligence (AI) and involves the development of algorithms and models that enable computers to learn and make predictions or decisions without being explicitly programmed [6]. The roots of machine learning can be traced back to the mid-20th century when pioneers like Alan Turing and Arthur Samuel laid the groundwork for the concept [7]. Initially, machine learning algorithms were relatively simple, focusing on rule-based systems and decision trees. However, as computational power increased and datasets became more extensive, the field evolved to encompass more complex technique [8].

In the early days of machine learning, the emphasis was on supervised learning, where algorithms were trained on labeled datasets to make predictions or classifications [9]. The advent of neural networks and the backpropagation algorithm in the 1980s contributed to significant advancements, but practical applications were limited due to computational constraints. The field experienced a renaissance in the 2010s, driven by the availability of large datasets and powerful GPUs. Deep learning, a subset of machine learning, gained prominence, enabling the training of complex neural networks with multiple layers, leading to breakthroughs in image recognition, natural language processing, and other domains [9, 10].

Machine learning is categorized into three main types: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning involves training a model on labeled data [11], while unsupervised learning deals with unlabeled data and focuses on discovering patterns and relationships [12, 13]. Reinforcement learning revolves around an agent learning by interacting with an environment and receiving feedback in the form of rewards or penalties [14]. The background of machine learning reflects a continuous journey of innovation and refinement, marked by the interplay of algorithmic developments, increased computing power, and the availability of diverse and extensive datasets. Regarding the types of machine learning as shown in Table 1.

Table 1. Types of machine learning.

Types of machine learning	Machine learning approach
Supervised learning	Training a model on labeled data
Unsupervised learning	Dealing with unlabelled data and focusing on discovering patterns and relationships
Reinforcement learning	Learning around an agent, receiving feedback in the form of rewards or punishments through interaction with the environment

3. Traditional ML Approaches to Handwriting Recognition

Handwriting recognition, a challenging task within the realm of image analysis, has been approached using various traditional machine learning (ML) techniques [15]. One common method is feature extraction [16], where relevant characteristics of handwritten text, such as line thickness, curvature, and spatial distribution, are identified. These features serve as the input for classical ML algorithms like Support Vector Machines (SVM) [17, 18] or k-Nearest Neighbors (k-NN). SVM, for instance, can create a hyperplane to separate different classes of handwritten characters [19, 20], while k-NN makes predictions based on the majority class among its nearest neighbors [19].

Another traditional approach involves Hidden Markov Models (HMMs), which have been applied to capture the temporal dependencies in handwriting sequences [13]. HMMs are probabilistic models that consider the likelihood of transitions between hidden states, making them suitable for modeling the dynamics of handwriting strokes [21]. By representing each character as a sequence of

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states, HMMs can be trained to recognize patterns and transitions, facilitating the identification of handwritten characters.

Ensemble methods, such as Random Forests or AdaBoost, have also found application in handwriting recognition. These techniques combine the strengths of multiple weak learners to create a robust and accurate model[22]. In the context of handwriting recognition, ensemble methods can integrate diverse features and classifiers to enhance overall performance [23], mitigating the impact of variability in writing styles.

Feature engineering plays a crucial role in traditional ML approaches to handwriting recognition. Researchers and practitioners design and select relevant features that encapsulate the distinctive aspects of handwriting. The success of these approaches depends heavily on the ability to extract discriminative features and design effective classifiers [24]. While traditional ML methods have made significant contributions to handwriting recognition, the field has witnessed a paradigm shift with the rise of deep learning, which has demonstrated superior performance in capturing intricate patterns and representations in handwritten text. The traditional ML handwriting recognition method is shown in Figure 1.

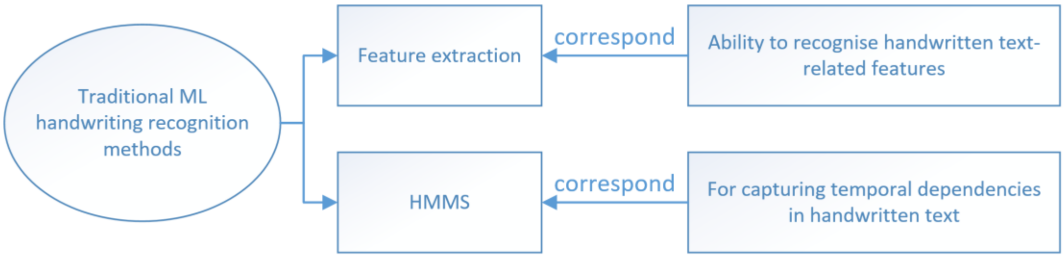

Figure 1. Traditional ML handwriting recognition methods.

4. Deep Learning Approaches to Handwriting Recognition

The advent of deep learning [25, 26] has revolutionized the field of handwriting recognition, offering powerful solutions that surpass the capabilities of traditional machine learning methods [27]. Convolutional Neural Networks (CNNs) have played a pivotal role in this transformation [23]. CNNs excel at learning hierarchical representations of input data, making them well-suited for image-based tasks like handwriting recognition [28]. In the context of character recognition, CNNs can automatically extract relevant features from images of handwritten text, learning patterns at different levels of abstraction [29].

Recurrent Neural Networks (RNNs) have also been instrumental in advancing handwriting recognition, particularly in dealing with the sequential nature of handwriting. RNNs are designed to capture dependencies over time [30], making them effective for recognizing patterns in the temporal sequences of strokes and characters [31]. Long Short-Term Memory (LSTM) networks, a type of RNN, are commonly used to model the temporal dynamics of handwriting, allowing for more accurate recognition of cursive and connected writing styles.

One of the groundbreaking approaches in deep learning [32] for handwriting recognition is the use of sequence-to-sequence models with attention mechanisms. These models, often based on architectures like the Encoder-Decoder framework, are capable of taking in a sequence of input data (handwritten text) and generating an output sequence (recognized text) [33]. Attention mechanisms enable the model to focus on relevant parts of the input sequence during the decoding process, allowing for more precise and context-aware recognition [34].

Transfer learning is another key aspect of deep learning in handwriting recognition [35]. Pre-trained models [36] on large datasets, such as those for general image recognition, can be fine-tuned for handwriting-specific tasks with smaller datasets [37]. This transfer of knowledge from broader domains to handwriting recognition enhances the model's ability to recognize diverse writing styles and improves overall performance, especially in scenarios with limited labeled data [38].

The use of deep learning has significantly improved the accuracy and robustness of handwriting recognition systems [39]. Neural networks can automatically learn intricate features and representations from raw data [40], reducing the need for manual feature engineering. However, challenges remain, such as the requirement for large labeled datasets, computational resources, and potential biases in the training data. As deep learning techniques continue to evolve, they are likely to play an increasingly crucial role in advancing the state-of-the-art in handwriting recognition. Regarding modules for deep learning methods as shown in Table 2.

Table 2. Modules for deep learning method.

Module	Correspond	Vantage
CNNs	Play a key role in changing the field of handwriting recognition	Expertise in learning hierarchical representations of input data makes them well suited for image-based tasks
RNNs	Advancing handwriting recognition	Capturing transformations over time allows them to efficiently recognize patterns in time series of strokes and characters
The use of sequence-to-sequence models with attention mechanisms	A pioneering approach in handwriting recognition	Ability to focus on the relevant part of the input sequence during decoding for more accurate perceptual recognition
Transfer learning	Key aspects of deep learning in handwriting recognition	Can be fine-tuned for handwriting-specific tasks with smaller data sets, improved overall performance

5. Common Handwriting Datasets

The development and evaluation of handwriting recognition systems heavily rely on the availability of diverse and well-annotated datasets. These datasets serve as benchmarks for researchers and practitioners to assess the performance of different algorithms and models. One widely used dataset in the field of handwriting recognition is the IAM Handwriting Database. The IAM dataset contains samples of English text written by various individuals, capturing a range of writing styles and variability. It includes both unconstrained text, such as sentences, as well as isolated words and lines, making it suitable for evaluating systems in real-world scenarios.

Another notable dataset is the CEDAR (Center for Document Analysis and Recognition) Benchmark Database. The CEDAR dataset encompasses a comprehensive collection of handwritten forms, including historical documents [41], census forms, and other document types. It is particularly valuable for assessing the performance of handwriting recognition systems in document analysis and processing tasks [41, 42]. The dataset offers a mix of challenges, including different writing styles, noise, and variations in document layout.

The RIMES dataset, derived from the French National Railway Company (SNCF) database, is focused on unconstrained handwriting recognition. It consists of handwritten text samples in both

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Latin and Arabic scripts, covering various contexts such as letters, administrative documents, and invoices [43]. The diversity of writing styles and the inclusion of multiple languages make the RIMES dataset a valuable resource for training and evaluating handwriting recognition systems in multilingual and multicultural contexts.

In addition to these, the MNIST dataset, although primarily known for digit recognition, has been influential in the early development of handwriting recognition algorithms. MNIST consists of 28x28 pixel grayscale images of handwritten digits, providing a simple yet effective benchmark for character recognition tasks [44, 45]. While not as complex as datasets specifically designed for handwriting recognition, MNIST has served as a starting point for researchers entering the field and exploring basic principles of image-based recognition [46].

These datasets, among others, have played a crucial role in advancing the state-of-the-art in handwriting recognition. As the field continues to evolve, the need for more extensive and diverse datasets becomes apparent to address the challenges posed by real-world applications and the variability in individual writing styles. Common handwritten datasets are categorised as shown in Figure 2, ingredient and specificities of common handwritten datasets are as shown in Table 3.

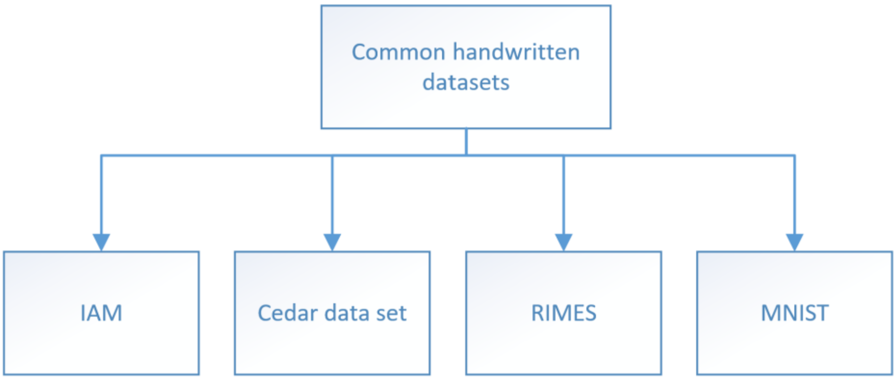

Figure 2. Common handwritten datasets.

Table 3. Common handwritten datasets.

Common handwritten dataset	Ingredient	Specificities
IAM	Unconstrained text, Samples of English texts prepared by different individuals	Suitable for evaluating systems in realistic scenarios
Cedar data set	Comprehensive collection of handwritten forms, historical documents, census forms and other types of forms	Evaluate the performance of handwriting recognition systems in online document analysis and processing tasks.
RIMES	Sample handwritten text in Latin and Arabic and various situations	Effective training and evaluation of handwriting recognition systems in multilingual and multicultural contexts

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MNIST	28x28 pixel grayscale image of handwritten digits	Provides a simple and effective benchmark for character recognition tasks

6. Challenges of Handwriting Recognition

Handwriting recognition, also known as Handwriting Optical Character Recognition (HOCR), faces several challenges that impact its accuracy and efficiency. One significant challenge lies in the inherent variability of human handwriting. Individuals exhibit diverse writing styles, making it difficult to create a universal model that accurately recognizes all variations. Factors such as the size, slant, and spacing of characters further contribute to the complexity of the recognition process [47].

Another challenge is the presence of noise and distortions in handwritten text. Environmental conditions, writing tools, and the medium on which the text is written can introduce irregularities, smudges, or uneven strokes that complicate the task of accurately identifying characters. Advanced algorithms and machine learning techniques are employed to mitigate these issues [48], but achieving complete robustness remains an ongoing challenge.

The lack of standardized datasets poses a third obstacle. Unlike printed text, which follows specific fonts and formatting, handwritten samples lack consistency. Obtaining a comprehensive and diverse dataset that adequately represents the wide range of handwriting styles is essential for training accurate recognition models. Without such datasets, the performance of handwriting recognition systems may suffer when confronted with unfamiliar patterns.

Lastly, contextual understanding and language modeling present challenges in handwriting recognition [49]. Unlike isolated character recognition, understanding the context and meaning of a sequence of handwritten words or sentences requires more advanced natural language processing capabilities. Developing models that can accurately interpret the semantics of handwritten content is a complex task [50], especially when dealing with cursive writing or languages with complex character combinations [51]. Addressing these challenges is crucial for enhancing the overall performance and applicability of handwriting recognition systems in various domains, such as document processing, digital note-taking, and accessibility technologies. The challenges of handwriting recognition are shown in Figure 3.

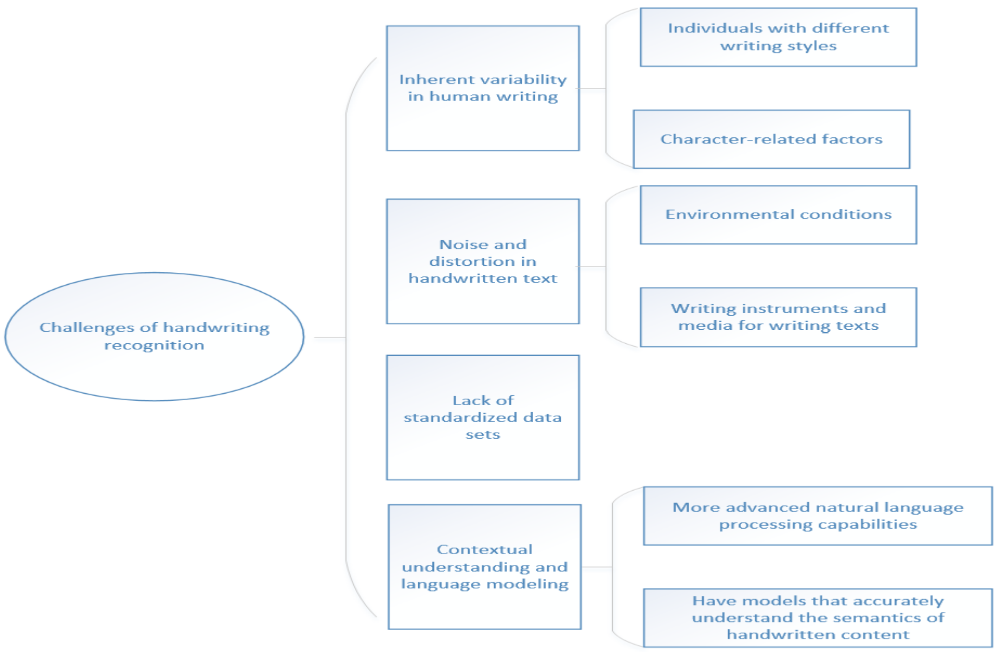

Figure 3. Challenges of handwriting recognition.

7. Conclusions

In conclusion, the field of handwriting recognition has witnessed a transformative journey with the evolution of machine learning methods. Traditional approaches, such as feature extraction and classical machine learning algorithms, laid the groundwork for recognizing handwritten characters, relying on engineered features and rule-based systems. However, the advent of deep learning marked a paradigm shift, empowering handwriting recognition systems with the ability to automatically learn intricate features and representations from raw data.

Deep learning approaches, particularly Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and sequence-to-sequence models, have demonstrated unprecedented success in capturing the complexities of handwriting. CNNs excel in extracting hierarchical features from image-based inputs, while RNNs, especially Long Short-Term Memory (LSTM) networks, adeptly model the temporal dependencies inherent in handwriting sequences. The incorporation of attention mechanisms in sequence-to-sequence models further enhanced the precision and context-awareness of handwriting recognition.

Transfer learning strategies, leveraging pre-trained models from broader domains, have addressed challenges related to limited labeled handwriting datasets, enabling models to adapt and generalize effectively. The use of common datasets like IAM, CEDAR, and RIMES has played a pivotal role in benchmarking the performance of different algorithms, fostering research and innovation in handwriting recognition.

Despite the remarkable progress achieved through machine learning methods, challenges persist, including the need for large labeled datasets, computational resources, and addressing potential biases. The ongoing evolution of deep learning techniques, coupled with advancements in data augmentation and unsupervised learning, holds promise for overcoming these challenges and further advancing the accuracy and applicability of handwriting recognition systems in diverse real-world scenarios. As research continues to push the boundaries of what is achievable, machine learning methods remain at the forefront of unlocking the full potential of automated handwriting recognition.

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References

1. K. Muthureka, U. S. Reddy, and B. Janet, "An improved customized CNN model for adaptive recognition of cerebral palsy people's handwritten digits in assessment," *International Journal of Multimedia Information Retrieval,* vol. 12, Article ID: 23, 2023.
2. Y. D. Zhang and S. Satapathy, "A seven-layer convolutional neural network for chest CT-based COVID-19 diagnosis using stochastic pooling," *IEEE Sensors Journal,* vol. 22, pp. 17573 - 17582, 2022.
3. S.-H. Wang and S. Fernandes, "AVNC: Attention-based VGG-style network for COVID-19 diagnosis by CBAM," *IEEE Sensors Journal,* vol. 22, pp. 17431 - 17438, 2022.
4. Y. Zhang, "Feature Extraction of Brain MRI by Stationary Wavelet Transform and its Applications," *Journal of Biological Systems,* vol. 18, pp. 115-132, 2010.
5. Y. Zhang, "Pathological brain detection in MRI scanning by wavelet packet Tsallis entropy and fuzzy support vector machine," *SpringerPlus,* vol. 4, Article ID: 716, 2015.
6. T. R. Prasad, S. Manvinder, G. A. Kumar, P. Digvijay, P. B. Kumar, S. Aakifa, *et al.*, "Timely Prediction of Diabetes by Means of Machine Learning Practices," *Augmented Human Research,* vol. 8, 2023.
7. W. Guo, J. Liu, F. Dong, M. Song, L. Zoe, K. M. K. Hasan, *et al.*, "Review of machine learning and deep learning models for toxicity prediction. ," *Experimental biology and medicine (Maywood, N.J.),* pp. 15353702231209421-15353702231209421, 2023.
8. N. Talha, S. Nadeem, T. N. u. Haq, S. R. Nawaz, and B. M. Hussain, "A comprehensive strategy for phase detection of high entropy alloys: Machine learning and deep learning approaches " *Materials Today Communications,* vol. 37, 2023.
9. "Natural Language Processing; Findings from S. Mezgec and Co-Researchers Advance Knowledge in Natural Language Processing (Mixed deep learning and natural language processing method for fake-food

image recognition and standardization to help automated dietary assessment)," *Journal of Engineering*, pp. 3325-, 2018.

10. "Health and Medicine - Public Health Nutrition; New Findings on Public Health Nutrition Described by Investigators at JoZef Stefan Institute (Mixed Deep Learning and Natural Language Processing Method for Fake-food Image Recognition and Standardization To Help Automated Dietary Assessment) " *Technology News Focus*, 2020.
11. A. A. Shola, H. Yu, and K. Wu, "Sea level variability and modeling in the Gulf of Guinea using supervised machine learning " *Scientific Reports*, vol. 13, pp. 21318-21318, 2023.
12. Y. Sha, Y. Xu, Y. Wei, W. Xia, and C. Wang, "Reconstruction of incomplete flow fields based on unsupervised learning " *Ocean Engineering*, vol. 288, 2023.
13. B. Jodie, T. Wang, F. David, J. Zhuang, T. Akiko, and O. Kazushige, "Finding simplicity: unsupervised discovery of features, patterns, and order parameters via shift-invariant variational autoencoders," *Machine Learning: Science and Technology*, vol. 4, 2023.
14. H. Fabian and Okhrin Ostap, "Enhanced method for reinforcement learning based dynamic obstacle avoidance by assessment of collision risk " *Neurocomputing*, vol. 568, pp. 127097-, 2024.
15. H. Fang, J. Cao, L. Cai, T. Zhou, and M. Wang, "The recognition of plastic bottle using linear multi hierarchical SVM classifier " *Journal of Intelligent & Fuzzy Systems*, vol. 40, pp. 11509-11522, 2021.
16. L. Pan, Z. Tang, S. Wang, and A. Song, "Cross-subject emotion recognition using hierarchical feature optimization and SVM with multi-kernel collaboration.," *Physiological measurement*, 2023.
17. Y. Zhang, "Detection of Alzheimer's disease and mild cognitive impairment based on structural volumetric MR images using 3D-DWT and WTA-KSVM trained by PSOTVAC," *Biomedical Signal Processing and Control*, vol. 21, pp. 58-73, 2015.
18. S. Wang, "Detection of Dendritic Spines using Wavelet Packet Entropy and Fuzzy Support Vector Machine," *CNS & Neurological Disorders - Drug Targets*, vol. 16, pp. 116-121, 2017.
19. C. Liu, "Optimization of negative sample selection for landslide susceptibility mapping based on machine learning using K-means-KNN algorithm " *Earth Science Informatics*, vol. 16, pp. 4131-4152, 2023.
20. R. Neelam, S. Vikas, and T. A. Kr., "Prioritizing software regression testing using reinforcement learning and hidden Markov model " *International Journal of Computers and Applications*, vol. 45, pp. 748-754, 2023.
21. X. Tang, "A Latent Hidden Markov Model for Process Data.," *Psychometrika*, 2023.
22. K. Satoshi, Y. Masanori, T. Ryo, Y. Shiori, K.-K. Hiromi, Y. Hiroe, *et al.*, "Dual ensemble approach to predict rice heading date by integrating multiple rice phenology models and machine learning-based genetic parameter regression models " *Agricultural and Forest Meteorology*, vol. 344, 2024.
23. A. S. Sohail, M. Zahid, A. I. Ahmad, and Y. R. Mehmood, "A Novel Technique for Handwritten Digit Recognition Using Deep Learning " *Journal of Sensors*, vol. 2023, 2023.
24. C. Ilya, G. Andris, and W. Hendrik, "Feature Engineering with Regularity Structures " *Journal of Scientific Computing*, vol. 98, 2023.
25. Y. Zhang and J. M. Gorriz, "Deep Learning in Medical Image Analysis," *Journal of Imaging*, vol. 7, p. 74, 2021.
26. Y. D. Zhang, "Pseudo Zernike Moment and Deep Stacked Sparse Autoencoder for COVID-19 Diagnosis," *CMC-Computers Materials & Continua*, vol. 69, pp. 3145-3162, 2021.
27. L. S. John, K. S. Deepa, E. A. Shamila, S. Dahli, and J. A., "An ensembled method for air quality monitoring and control using machine learning " *Measurement: Sensors*, vol. 30, 2023.
28. A. Nidhal, "Handwritten digits recognition using transfer learning," *Computers and Electrical Engineering*, vol. 106, 2023.
29. R. Amin, M. S. Reza, Y. Okuyama, Y. Tomioka, and J. Shin, "A Fine-Tuned Hybrid Stacked CNN to Improve Bengali Handwritten Digit Recognition " *Electronics*, vol. 12, 2023.
30. G. Yang, B. Tang, and S. Cao, "Research on Residual Convolutional Neural Network for Handwritten Digit Recognition " *Journal of Electronics and Information Science*, vol. 8, 2023.
31. H. Matin, M. Anthony, H. Seyedmajid, and G. Raju, "Inception Recurrent Neural Network Architecture for Video Frame Prediction " *SN Computer Science*, vol. 4, 2022.
32. Y. Zhang and M. A. Khan, "SNELM: squeezeNet-guided ELM for COVID-19 recognition," *Computer Systems Science and Engineering*, vol. 46, pp. 13-26, 2023.
33. M. S. Mahmoud and N. Negied, "A Novel Deep-learning based Approach for Automatic Diacritization of Arabic Poems using Sequence-to-Sequence Model " *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 14, 2023.
34. B. G. L. Anand and B. Srinivasu, "Deep learning based sequence to sequence model for abstractive telugu text summarization " *Multimedia Tools and Applications*, vol. 82, pp. 17075-17096, 2022.
35. B. Yousra and G. Zouhair, "Handwritten Digit Recognition System based on CNN and SVM " *Signal & Image Processing : An International Journal*, vol. 13, pp. 11-17, 2022.
36. K. D. M., R. M. A., and K. I. S., "Active Learning and Transfer Learning for Document Segmentation " *Programming and Computer Software*, vol. 49, pp. 566-573, 2023.

37. Y. Jing, S. Mohammad, Y. P. Lip, K. A. Ayub, A. Muhammad, and M. Zohreh, "DT2F-TLNet: A novel text-independent writer identification and verification model using a combination of deep type-2 fuzzy architecture and Transfer Learning networks based on handwriting data " *Expert Systems With Applications,* vol. 242, pp. 122704-, 2024.
38. G. Palak and R. Rinkle, "Comparative Analysis of Machine Learning, Ensemble Learning and Deep Learning Classifiers for Parkinson's Disease Detection " *SN Computer Science,* vol. 5, 2023.
39. M. Theron, T. Miho, and G. Nicole, "Faculty publication trends in a Japanese national university: a diachronic document analysis " *Journal of Pharmaceutical Health Care and Sciences,* vol. 9, pp. 34-34, 2023.
40. C. K. Lynn, N. E. E, S. Katherine, O. Rachel, and S. K. Scott, "Technology - Cybernetics; Researchers at University of Technology Have Reported New Data on Cybernetics (Feature Set Evaluation for Offline Handwriting Recognition Systems: Application to the Recurrent Neural Network Model) " *Computers, Networks & Communications*, 2017.
41. A. Maqqor, A. Halli, K. Satori, and H. Tairi, "Offline Arabic Handwriting Recognition System Based on the Combination of Multiple Semi-Continuous HMMs " *International Review on Computers and Software IRECOS,* vol. 10, pp. 677-683, 2015.
42. A.-w. Ebrahim and G. Rozaida, "Threshold center-symmetric local binary convolutional neural networks for bilingual handwritten digit recognition," *Knowledge-Based Systems,* vol. 259, 2023.
43. D. Swain, B. Parmar, H. Shah, and A. Gandhi, "Improved handwritten digit recognition using artificial neural networks " *International Journal of Computing Science and Mathematics,* vol. 17, pp. 353-370, 2023.
44. N. Olivia, K. Jaeseok, B. M. Zain, and C. Filippo, "Image Classification Using Multiple Convolutional Neural Networks on the Fashion-MNIST Dataset," *Sensors,* vol. 22, pp. 9544-9544, 2022.
45. B. Hu, Z. Meng, Y. Chen, Y. Jiang, C. Chang, Z. Ke, *et al.*, "Intelligent and Accurate Tobacco Curing via Image Recognition and Data Analysis " *Journal of Circuits, Systems and Computers,* vol. 32, 2023.
46. G. Monica, C. Alka, and P. Jyotsna, "Analysis of Text Identification Techniques Using Scene Text and Optical Character Recognition " *International Journal of Computer Vision and Image Processing (IJCVIP),* vol. 11, pp. 39-62, 2021.
47. V. K. Sonthi, S. Nagarajan, and N. Krishnaraj, "Automated Telugu Printed and Handwritten Character Recognition in Single Image using Aquila Optimizer based Deep Learning Model " *International Journal of Advanced Computer Science and Applications (IJACSA),* vol. 12, 2021.
48. S. Albahli, M. Nawaz, A. Javed, and A. Irtaza, "An improved faster-RCNN model for handwritten character recognition " *Arabian Journal for Science and Engineering,* vol. 46, pp. 1-15, 2021.
49. G. Rohan, H. Nina, H. Ming, Y. Guo, S. D. F, R. Lior, *et al.*, "Keyphrase Identification Using Minimal Labeled Data with Hierarchical Context and Transfer Learning. ," *medRxiv : the preprint server for health sciences*, 2023.
50. S. Wang, "Grad-CAM: understanding AI models," *Computers, Materials & Continua,* vol. 76, pp. 1321-1324, 2023.
51. A. A. P, M. K, and S. M. Idicula, "An Improved Word Representation for Deep Learning Based NER in Indian Languages," *Information,* vol. 10, pp. 186-186, 2019.