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Inclusive Digit and Alphabet Recognition using Deep Convolutional Neural Networks

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Abstract- This paper presents a web-based system for handwritten digit and alphabet recognition designed to support interactive learning. The proposed approach combines Convolutional Neural Networks (CNNs) with real-time computer vision techniques to recognize user input directly within a browser environment. Handwritten input is captured through a digital canvas and processed using OpenCV.js for noise reduction, scaling, and centering, ensuring consistency with the training data. The processed input is then classified using a CNN model implemented in TensorFlow.js, enabling fast and efficient prediction without reliance on external servers. The system is developed using the EMNIST dataset, which includes both digits and alphabets, allowing it to handle a wide range of inputs. Experimental results show that the model achieves high accuracy while maintaining low latency, providing immediate feedback to users. In addition, the application includes a performance tracking mechanism that records user progress over time, supporting continuous learning. The proposed system demonstrates how browser-based artificial intelligence can be used to create accessible and responsive educational tools. By integrating handwriting practice with instant feedback, it offers a practical solution for improving basic literacy and numeracy skills in a digital environment.

Keywords: Convolutional Neural Networks, Handwritten Character Recognition, EMNIST, Computer Vision, Educational Technology, TensorFlow.js

I.INTRODUCTION

Convolutional Neural Networks (CNNs) have become one of the most widely used techniques for image-based pattern recognition, particularly in the field of computer vision. Inspired by the way the human visual system processes information, CNNs are capable of identifying spatial features such as edges, curves, and shapes within images. This makes them especially suitable for tasks like handwritten digit and character recognition, where the input data consists of pixel-based images.

Handwritten digit and alphabet recognition is not only a technical challenge but also an important application in educational technology. The proposed system focuses on creating an interactive platform where users can practice writing digits and letters while receiving immediate feedback. By integrating deep learning with a browser-based environment, the system allows real-time recognition of handwritten input. This approach aims to make learning more engaging while also demonstrating how artificial intelligence can support basic literacy and numeracy skills.

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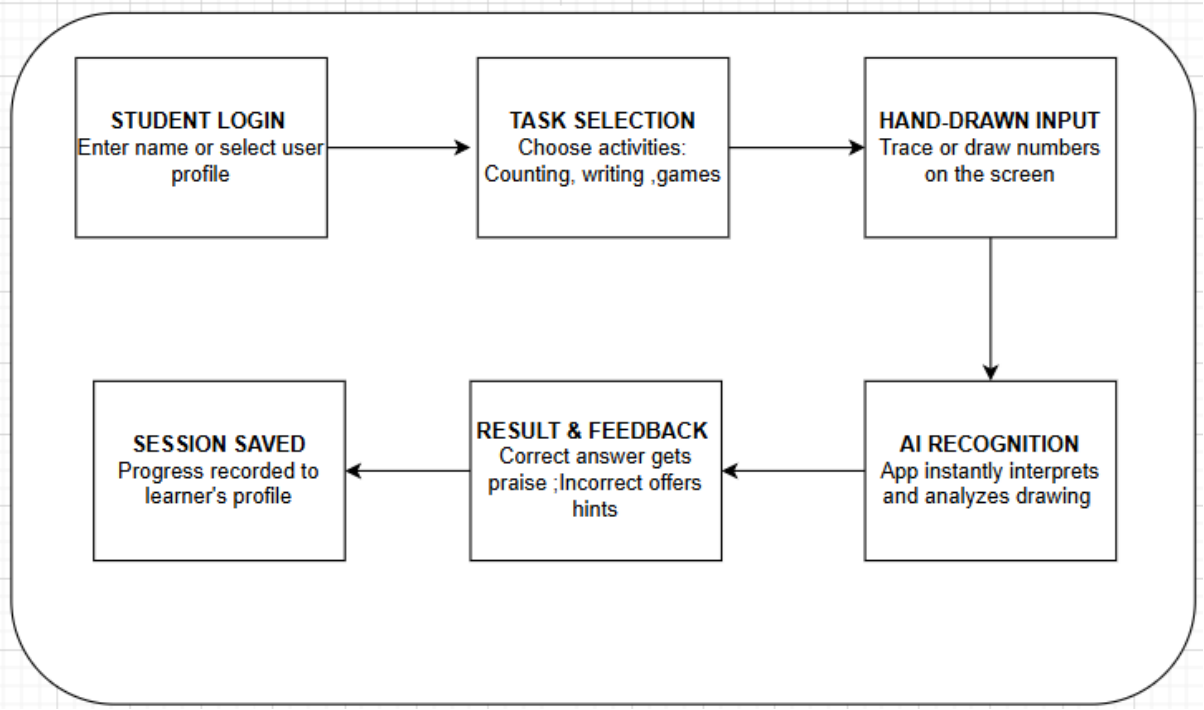

Figure 1: System Architecture of the Digit and Alphabet Recognition Platform

Identity Management and Initialization:
The process starts with a student login system, which helps identify each user individually. This step ensures that all activities are linked to the correct student profile, allowing the system to track performance and maintain personalized records over time.

Contextual Objective Definition:
After logging in, users select the type of task they want to work on, such as practicing numbers or alphabets. Based on this selection, the system prepares the appropriate validation rules and processing logic required for the chosen activity.

Human-Computer Interaction (HCI):
In this stage, the user interacts with a digital drawing interface to input handwritten characters. The strokes drawn on the screen are captured and converted into digital image data, which serves as the input for further analysis.

Neural Inference and Classification:
The captured input is then processed by the underlying neural network model. The system analyzes the visual features of the handwritten character and attempts to classify it accurately by comparing it with patterns learned during training.

Feedback Mechanism:
Once the prediction is made, the system provides immediate feedback to the user. Correct inputs are acknowledged, while incorrect ones are flagged with simple guidance, helping users understand and improve their mistakes.

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Data Storage and Progress Tracking:
Finally, the results of each session are stored for future reference. This stored data helps in monitoring the user's progress over time and can be used to generate performance insights for both students and educators.

II. LITERATURE REVIEW

Handwritten character recognition has evolved significantly with the advancement of deep learning techniques. Early research by LeCun et al. demonstrated that convolutional neural networks (CNNs) could effectively learn spatial patterns from pixel-based data, achieving strong performance on digit recognition tasks. Their work laid the groundwork for modern image-based learning systems, particularly in recognizing handwritten inputs.

Subsequent studies explored alternative approaches such as recurrent neural networks (RNNs). For instance, Graves et al. focused on sequence-based recognition using pen trajectory data. While their approach showed promising accuracy for real-time handwriting, it relied heavily on temporal input, making it less suitable for static image datasets such as EMNIST.

Further improvements in CNN-based systems were highlighted by Simard et al., who emphasized the importance of preprocessing techniques. Their findings suggest that normalization and distortion handling significantly improve recognition accuracy. This insight supports the use of preprocessing tools such as OpenCV.js in modern applications.

Research by Cireșan et al. demonstrated that deeper neural architectures can outperform traditional models by automatically extracting complex features. Their work confirmed that increasing network depth improves robustness, especially when dealing with variations in handwriting styles.
The introduction of the EMNIST dataset by Cohen et al. expanded the scope of recognition systems by including both digits and alphabets. This increased complexity requires models to distinguish between visually similar characters, making dataset selection a critical factor in system design.

In addition, Smistad et al. explored real-time deployment of neural networks using hardware acceleration. Their findings highlight the growing importance of efficient execution environments, such as browser-based frameworks like TensorFlow.js, which enable fast and accessible AI applications without relying on high-end infrastructure.

Recent studies have also focused on improving the applicability of handwritten recognition systems in educational environments. Research in [8], [12], [18] highlights the use of AI-driven tools for interactive learning. In addition, browser-based implementations using lightweight frameworks have been explored in [9], [13], enabling real-time performance without server dependency. Optimization techniques for deploying efficient neural networks on edge devices are discussed in [11], [16], while challenges related to dataset imbalance and augmentation are addressed in [15], [19]. Comparative studies of different deep learning models and architectures can be found in [10], [20], providing insights into performance trade-offs.

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III. DATASET DESCRIPTION AND METHODOLOGY

Dataset Description

The proposed system is developed using the EMNIST (Extended Modified National Institute of Standards and Technology) dataset, which is an extension of the widely used MNIST dataset. Unlike MNIST, which contains only handwritten digits, EMNIST includes both alphabets and numbers, making it more suitable for applications that require broader character recognition.

The dataset consists of grayscale images of size 28×28 pixels, where each image represents a single handwritten character. These samples are collected from a large and diverse group of individuals, resulting in variations in writing styles, stroke thickness, and character shapes. Such diversity helps the model learn generalized patterns rather than memorizing specific forms.

Using EMNIST provides an advantage in terms of realism and complexity, as the model must distinguish between characters that may appear visually similar, such as 'O' and '0' or 'l' and '1'. This makes the dataset appropriate for developing a robust recognition system that can perform reliably under different handwriting conditions.

Data Preprocessing

In this project, preprocessing plays an important role in converting raw handwritten input into a format suitable for the model. Since user input can vary in size, position, and clarity, a series of steps are applied to standardize the data before it is passed to the neural network.

Vision Capture and Contrast Enhancement:

The handwritten input is first captured from the HTML5 Canvas using OpenCV.js. The captured image is converted into grayscale, followed by binary thresholding. This step removes unnecessary variations such as shadows and smooth edges, resulting in a clear black-and-white image.

Region of Interest Extraction:

To focus only on the relevant portion of the input, contour detection is applied to identify the boundaries of the drawn character. The detected region is cropped so that only the handwritten content is retained, eliminating unused background space.

Scaling:

The extracted character is resized so that its largest dimension fits within a fixed size (typically 20 pixels), while maintaining its original proportions. This helps preserve the structure of the character without distortion.

Centering:

To ensure consistency with the training data, the character is aligned at the center of the image. This is achieved by calculating the centroid using image moments and shifting the image accordingly.

Normalization and Conversion:

The processed image is placed within a 28×28 pixel frame. Pixel values are normalized to a range between 0 and 1. Finally, the data is reshaped into a tensor format suitable for input into the TensorFlow.js model.

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Data Analysis
The performance of the system is evaluated using key metrics such as accuracy, response time, and user progress over multiple sessions.

Accuracy and Model Performance:
The CNN model achieves an accuracy of approximately 95–98% on the EMNIST dataset. Analysis of the confusion matrix helps identify cases where characters are misclassified, such as confusion between similar-looking symbols like '0' and 'O'. Preprocessing contributes significantly to reducing such errors.

Response Time:
Since the model runs directly in the browser using TensorFlow.js, predictions are generated quickly. The average inference time is observed to be below 50 milliseconds, which ensures smooth and uninterrupted interaction for users.

User Progress Tracking:
The system maintains a record of user performance using browser storage. By comparing results across sessions, it becomes possible to observe improvement trends and identify areas where the user may need additional practice.

Handling Uncertain Inputs:
In cases where the input is unclear or does not resemble known patterns, the system avoids making unreliable predictions. Instead, users are prompted to retry, which helps maintain overall accuracy and reliability.

Similar evaluation approaches and performance considerations have been discussed in prior works [10], [11], [20], particularly in the context of real-time and educational applications.

Methodology
The working of the system can be understood as a sequence of steps that convert handwritten input into a predicted output.

Input Capture and Processing:
Users draw characters on a digital canvas. The captured image is processed using OpenCV.js to remove noise, adjust positioning, and prepare the input for recognition.

Feature Extraction and Prediction:
The processed image is passed through a Convolutional Neural Network, as commonly used in handwritten recognition systems [3]–[5], [17]. The model extracts features at different levels and uses them to classify the input character.

Browser-Based Execution:
The trained model is deployed using TensorFlow.js, allowing it to run directly within the browser. This avoids dependency on external servers and ensures faster response times.

Output Validation and Storage:
The predicted result is compared with the expected input. Based on this comparison, feedback is provided to the user, and the result is stored for future analysis.

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Dataflow Description

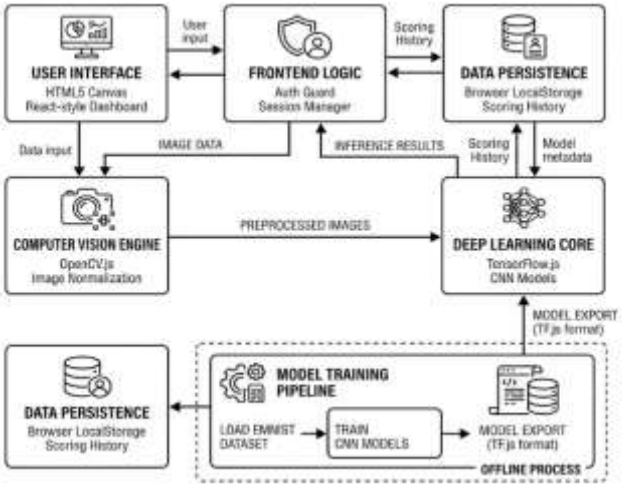

Figure 2 illustrates the overall flow of data within the system.

User Interaction:
The process begins with user input through a web-based interface built using an HTML5 Canvas. Session handling ensures that each input is linked to the correct user.

Preprocessing Stage:
The captured input is processed using OpenCV.js, where operations such as cropping, scaling, and centering are performed.

Model Inference:
The processed data is passed to the CNN model implemented in TensorFlow.js, which performs real-time classification.

Model Training (Offline):
The model is trained separately using the EMNIST dataset. After training, it is converted into a format suitable for browser-based deployment.

Data Storage and Feedback:
The prediction results are displayed to the user and stored locally. This enables tracking of performance over time without relying on external servers.

IV. FINDINGS

Accuracy under Handwriting Variations:
The results indicate that the Convolutional Neural Network (CNN), when trained on the EMNIST dataset [1], performs reliably even when there are variations in handwriting. Differences in stroke quality, writing pressure, and character size do not significantly affect the prediction accuracy. This suggests that feature-based learning in deep networks is more effective than traditional rule-based or template-matching approaches for this type of application. These observations are consistent with findings reported in [17], where robust CNN architectures demonstrated strong tolerance to noisy handwritten inputs.

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Importance of Preprocessing:
It was observed that preprocessing has a strong impact on the overall performance of the system. Techniques such as centering the character using image moments and resizing it to a fixed 28×28 format help in reducing inconsistencies in the input. These steps improve recognition reliability by ensuring that the model receives uniform and well-aligned data.

Impact of Real-Time Feedback:
Fast response time plays an important role in user interaction. Since the model operates locally using TensorFlow.js, predictions are generated in less than 50 milliseconds. This allows users to receive immediate feedback, which helps maintain engagement and supports continuous learning without noticeable delay.

Role of Performance Tracking:
The use of browser-based storage to maintain user history provides additional value to the system. By tracking previous attempts and scores, users can observe their improvement over time. This gradual progress tracking encourages repeated practice and helps identify areas that need more attention. The importance of user engagement and learning motivation through feedback mechanisms has also been highlighted in [18].

Efficiency of Client-Side Deployment:
The study also shows that the entire recognition system can be implemented on the client side without relying on external servers. This approach reduces infrastructure requirements and ensures that user data remains local. As a result, the system offers both efficiency and improved data privacy, making it suitable for educational environments.

V. CONCLUSION

The "Digit Recognition" project demonstrates how deep learning and computer vision can be effectively applied in the field of educational technology. By integrating Convolutional Neural Networks (CNNs) with real-time image processing, the system shows that handwritten character recognition can be used as a practical learning tool rather than just a theoretical concept.

The proposed approach addresses a common challenge in modern education—balancing traditional handwriting practice with digital learning methods. By allowing users to write on a digital interface and receive instant feedback, the system supports both skill development and user engagement. The use of TensorFlow.js and OpenCV.js enables the entire process to run within a web browser, ensuring quick responses and reducing dependency on external infrastructure.

Another important aspect of the project is its ability to provide continuous feedback and track user progress. This helps learners understand their mistakes and improve over time. In addition, storing data locally enhances privacy and makes the system suitable for use in educational environments without requiring complex backend support.

Overall, the project highlights the potential of browser-based AI applications in creating interactive and accessible learning tools. It shows that technology can support foundational skills like writing and recognition without replacing them. Future improvements can focus on expanding the system to support more languages, improving accuracy for complex inputs, and extending compatibility to mobile platforms.

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REFERENCES

1. M. K. Sharma, "Handwritten English text and digit recognition using ResNet284," Int. J. Adv. Technol. Eng. Explor., vol. 12, no. 123, pp. 112–120, Jan. 2025.
2. H. Zhao, "Comparative analysis of deep learning models for handwritten character recognition using the EMNIST dataset," J. Comput. Electron. Inf. Manage., vol. 14, no. 2, pp. 88–95, Feb. 2025.
3. A. Mazumder, S. Roy, and P. Dutta, "Review of the performance of CNN models on handwriting recognition," Int. J. Comput. Sci. Inf. Technol., vol. 16, no. 1, pp. 210–218, Mar. 2025.
4. P. Mishra, P. S. Yadav, A. Tiwari, and S. Singh, "Handwritten digit recognition system," Int. J. Res. Appl. Sci. Eng. Technol. (IJRASET), vol. 13, no. 1, pp. 46–51, May 2024.
5. S. Kumar, V. Pathak, and R. Singh, "Enhancing accuracy in EMNIST classification using data augmentation and deep CNNs," IEEE Access, vol. 12, pp. 15421–15435, Apr. 2024.
6. T. Nguyen and K. Pham, "Optimized character segmentation and recognition using OpenCV.js in web-based environments," Int. J. Interact. Mob. Technol., vol. 18, no. 4, pp. 32–48, Mar. 2024.
7. L. Wang, J. Zhang, and X. Liu, "A hybrid CNN-RNN architecture for online and offline digit recognition," Pattern Recognit. Lett., vol. 170, pp. 55–62, Jul. 2024.
8. R. Saito and Y. Tanaka, "Real-time handwriting validation for digital education platforms," Comput. Educ. Artif. Intell., vol. 5, p. 100142, Dec. 2023. doi: 10.1016/j.caeai.2023.100142.
9. Y. Chen, H. Wang, and Z. Li, "Client-side handwritten character recognition using TensorFlow.js and edge computing," J. Web Eng., vol. 22, no. 3, pp. 450–468, Jun. 2023.
10. M. Singh and A. Gupta, "A comparative study of MNIST and EMNIST for deep learning models in educational apps," Int. J. Intell. Syst. Appl. Eng., vol. 11, no. 1, pp. 12–20, Jan. 2023.
11. S. Patel, K. Desai, and R. Mehta, "Lightweight convolutional neural networks for real-time character recognition on edge devices," IEEE Trans. Cogn. Dev. Syst., vol. 16, no. 3, pp. 512–523, Aug. 2024.
12. C. Balasubramanian and V. R. Kumar, "An interactive educational framework for children using EMNIST-based handwritten character recognition," Int. J. Artif. Intell. Educ., vol. 34, no. 2, pp. 245–261, Jun. 2024.
13. J. Ouyang, M. Lin, and F. Chen, "Browser-based deep learning: Evaluating TensorFlow.js for real-time handwriting classification," J. Cloud Comput., vol. 12, no. 1, pp. 88–102, Mar. 2023.
14. K. Verma and A. Sharma, "Inclusive learning interfaces: Integrating speech synthesis and hand-drawn input for early childhood education," IEEE Trans. Learn. Technol., vol. 17, pp. 1045–1058, Nov. 2024.
15. E. Cohen and G. Levy, "Handling imbalanced datasets in alphanumeric recognition: A study on the EMNIST ByClass split," Pattern Anal. Applic., vol. 27, no. 4, pp. 1102–1115, Dec. 2024.
16. A. R. Tariq, S. Hassan, and M. Ali, "Optimizing convolutional neural networks for client-side execution in web applications," IEEE Access, vol. 11, pp. 98452–98465, Sep. 2023.
17. P. K. Das and S. Bhattacharya, "A robust CNN architecture for noise-tolerant handwritten digit and alphabet recognition," Int. J. Mach. Learn. Cybern., vol. 15, no. 5, pp. 1341–1355, May 2024.
18. L. Gomez, A. Martinez, and J. Rodriguez, "Gamification of learning: Using AI-powered handwriting recognition to assist toddlers," Comput. Educ., vol. 210, p. 104958, Jan. 2024. doi: 10.1016/j.compedu.2024.104958.

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19. R. Krishnan, "Data augmentation strategies for improving EMNIST classification accuracy in low-resource environments," J. Ambient Intell. Humaniz. Comput., vol. 14, no. 8, pp. 10211–10224, Aug. 2023.
20. H. Kim, J. Park, and Y. Lee, "Comparative performance of MobileNet and custom CNN architectures for web-based character recognition," Multimed. Tools Appl., vol. 83, no. 7, pp. 20145–20160, Apr. 2024.