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An Intelligent AI-Based Framework for Handwritten Character Recognition

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ABSTRACT

Handwritten Character Recognition (HCR) remains a fundamental yet challenging problem in pattern recognition due to variations in writing styles, distortions, noise, and inter-class similarity. This study proposes an intelligent AI-based framework for robust handwritten character recognition using a Convolutional Neural Network (CNN). The model is trained and evaluated on a self-curated dataset comprising 13,640 grayscale images representing 62-character classes, including digits (0–9), lowercase letters (a–z), and uppercase letters (A–Z). Images are standardized to a resolution of 28×28 pixels and normalized to enhance learning efficiency. The proposed CNN architecture leverages hierarchical feature extraction through multiple convolutional and pooling layers, followed by dense layers for classification. Experimental results demonstrate a recognition accuracy of approximately 93%, indicating strong generalization capability despite handwriting variability. The proposed framework emphasizes automated feature learning, eliminating the dependency on handcrafted descriptors traditionally used in character recognition systems. The model exhibits strong adaptability across diverse handwriting patterns, demonstrating robustness to intra-class variations. Furthermore, the lightweight CNN architecture ensures computational efficiency, making the system suitable for real-time applications and deployment in resource-constrained environments. The study also highlights the critical role of dataset quality, preprocessing strategies, and normalization techniques in improving recognition performance. Overall, the findings confirm that deep learning-driven approaches offer a reliable, scalable, and efficient solution for handwritten character recognition.

Keywords: *Handwritten Character Recognition, Convolutional Neural Network (CNN), Deep Learning, Image Classification, Pattern Recognition.*

1. INTRODUCTION

Handwritten Character Recognition (HCR) plays a vital role in numerous real-world applications, including document digitization, postal automation, bank cheque processing, form analysis, historical manuscript preservation, and intelligent human-computer interaction systems. Despite significant advancements, accurate recognition of handwritten characters remains a challenging problem due to inconsistencies in writing styles, stroke patterns, orientation, character spacing, and noise artifacts. Traditional recognition systems relied heavily on handcrafted feature extraction techniques such as edge detection, zoning methods, projection histograms, and geometric descriptors. While these approaches provided moderate success, they often struggled to generalize across diverse handwriting styles and required extensive domain expertise. The emergence of Artificial Intelligence (AI) and deep learning has transformed the landscape of pattern recognition by enabling models to automatically learn discriminative features directly from raw image data. Recent advancements in deep learning have significantly reshaped the field of image-based pattern recognition, allowing systems to capture complex spatial dependencies and visual structures. Unlike conventional machine learning techniques, deep neural networks can model intricate variations in data without manual feature engineering. The variability inherent in human handwriting including differences in stroke formation, thickness, curvature, and alignment necessitates intelligent systems capable of adaptive learning. In this context, Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image classification tasks by automatically extracting hierarchical visual features. CNNs efficiently learn low-level features such as edges and textures, mid-level representations like curves and shapes, and high-level abstractions capturing character structures. Motivated by these capabilities, this research proposes an intelligent AI-based framework utilizing a CNN for robust handwritten character recognition. Unlike benchmark datasets, self-curated datasets offer practical relevance by incorporating realistic handwriting variations, making the study experimentally valuable and application oriented. This research leverages a custom dataset containing 13,640 grayscale images across 62-character categories, reflecting real-world handwriting diversity. The proposed framework aims to develop a reliable recognition system capable of handling complex variations while maintaining computational efficiency and scalability.

2. RELATED WORKS

Handwritten Character Recognition has been extensively explored within computer vision and pattern recognition research. Early systems primarily employed statistical classifiers combined with handcrafted features. Techniques such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Artificial Neural Networks (ANN), and Hidden Markov Models (HMM) were widely adopted. With the advent of deep learning, Convolutional Neural Networks (CNNs) significantly transformed the landscape of character recognition systems. Unlike conventional techniques, CNNs enable automatic hierarchical feature learning directly from raw image data, thereby eliminating the dependency on handcrafted descriptors. Numerous studies have reported substantial performance improvements using CNN-based architectures for digit recognition, alphanumeric classification, and multilingual character recognition tasks. CNNs effectively capture spatial relationships and local visual patterns, allowing models to learn discriminative representations such as edges, textures, curves, and character structures. Pooling operations further enhance translation invariance, improving robustness against distortions and writing variability. Recent advancements have focused on deeper and more sophisticated architectures, including Residual Networks (ResNet), EfficientNet, and attention-based models. These approaches enhance representational capacity and improve classification accuracy, particularly in challenging scenarios involving noisy images or visually similar characters. Researchers have also emphasized the critical role of dataset diversity, preprocessing strategies, and normalization techniques in improving model performance. Benchmark datasets, while useful for standard evaluation, often lack the variability observed in real-world handwriting, prompting the development of custom datasets for practical applications. Despite considerable progress, challenges remain in distinguishing characters with high visual similarity, motivating continued research into optimized architectures and hybrid learning frameworks. [1] HCR-Net introduces a script-independent deep learning network using partial transfer learning from pre-trained VGG16 layers, achieving up to 11% performance gains on 40 datasets across 14 languages like Bangla, Hindi, and Arabic, with 34% fewer trainable parameters and rapid convergence. This framework sets a new direction for multilingual HCR by addressing handwriting variability without script-specific designs. A CRNN architecture combines CNN for feature extraction and RNN for sequence modeling, applied to IAM datasets, yielding low CER and WER rates while handling cursive styles effectively. Evaluations show steady accuracy improvements over epochs, outperforming HMMs due to automated feature learning. [3] This hybrid uses CNN for spatial features, BiLSTM for sequences, and CTC decoder, attaining 98.5-98.8% accuracy on IAM and RIMES datasets after preprocessing like binarization. It excels in real-world tasks like check reading by reducing manual feature needs. Leveraging sEMG sensors, SSDAE extracts sparse features for lowercase English letters, surpassing 94% accuracy via sparsity constraints and outperforming DWT methods. The pipeline handles multi-stroke gestures, advancing wearable HCR applications [4]. Research on intelligent AI-based frameworks for handwritten character recognition (HCR) has evolved rapidly, with HCR-Net presenting a script-independent deep learning model using partial transfer learning from VGG16, achieving up to 11% accuracy gains across 40 datasets in 14 languages like Bangla and Arabic while reducing trainable parameters by 34%. Similarly, CRNN architectures integrate CNNs for feature extraction and RNNs for sequence modeling on IAM datasets, delivering low character error rates (CER) and word error rates (WER) that surpass traditional HMMs by automating feature learning and handling cursive handwriting effectively. Hybrid CNN-BiLSTM-CTC models further advance this by combining spatial feature extraction with bidirectional sequence processing and connectionist temporal classification decoding, attaining 98.5-98.8% accuracy on IAM and RIMES after preprocessing steps like binarization, making them ideal for real-world applications such as check reading. Sensor-based approaches like SSDAE leverage sEMG signals for sparse feature extraction in lowercase English recognition, exceeding 94% accuracy and outperforming DWT methods for multi-stroke gestures in wearable HCR systems. CNN-RNN-BiGRU frameworks capture spatio-temporal dependencies on large datasets with minimal manual engineering, enhancing robustness for offline diverse handwriting styles. TamHNet's deep inception networks with residual connections achieve 99.8% accuracy for Tamil characters, addressing script-specific challenges. Neural network frameworks using pixel vector flattening and backpropagation via NumPy arrays enable efficient digit and character classification through stochastic gradients. Surveys on HTR trace progress from HMMs to Transformers, highlighting CNN-RNN hybrids, data augmentation, and transfer learning to overcome data scarcity in historical documents. ANN systems for student notes incorporate preprocessing and spell-checking, demonstrating neural superiority over conventional methods. Wearable deep feature hybrids reach 94.85% for multi-stroke recognition, shifting from template matching to end-to-end learning. Comprehensive SLRs reviewing 142 papers from 2000-2018 identify ML trends and gaps in script-independent designs. Belfort archive models using CRNN-BLSTM outperform HMMs with fewer parameters on French texts. CNN-LSTM-CTC on IAM yields 4.57% CER via augmentation for mixed scripts. CRNN edges out pure CNN on 370k-name datasets for variability. SLRs on handwritten OCR guide intelligent framework development for digitization. Physical document HCR via ML tackles scanned noise in offline systems. Surveys compare SVM, CNN, KNN, and HMM for HCR evolution. Offline/online ANN note systems emphasize preprocessing efficiency. Keyword search models hit 89-90% precision in noisy handwriting.

3. OVERVIEW OF HANDWRITTEN CHARACTERS

Handwritten characters represent one of the most natural and widely used forms of human communication. Unlike machine-printed text, handwritten characters exhibit significant variability due to differences in individual writing styles, stroke formation, pressure, orientation, spacing, and speed. These variations introduce substantial complexity in automated recognition systems, making handwritten character analysis a challenging problem in computer vision and pattern recognition. Handwritten characters can broadly be categorized into digits, lowercase letters, and uppercase letters, each possessing distinct structural properties. However, even within the same class, characters may appear differently depending on the writer's personal style. Factors such as slant, curvature, stroke thickness, incomplete formation, and overlapping strokes further increase intra-class variability. Additionally, visually similar characters such as 'O' and '0', 'l' and '1', or 'S' and '5' it creates inter-class ambiguity, complicating classification tasks.

From a computational perspective, handwritten characters are typically represented as image data, where recognition systems must identify discriminative visual patterns. These patterns include edges, corners, curves, intersections, and texture-based features. Variations caused by noise, distortions, and background artifacts further necessitate robust preprocessing and feature extraction mechanisms. Modern recognition frameworks leverage deep learning techniques, particularly Convolutional Neural Networks (CNNs), to automatically learn hierarchical feature representations that capture both local and global character structures. Understanding the inherent variability and structural complexity of handwritten characters is essential for designing accurate recognition systems. Effective character recognition models must accommodate style diversity while maintaining the ability to distinguish subtle visual differences. Consequently, handwritten character recognition remains an active research area with significant practical relevance across document analysis, education technology, authentication systems, and intelligent human-computer interaction applications.

2.1 DATASET

The dataset used in this study was manually collected to ensure a realistic representation and diversity of handwritten character patterns. A total of 13,640 handwritten character images were gathered, covering 62 distinct classes, including digits (0–9), lowercase letters (a–z), and uppercase letters (A–Z). Each class contains 220 samples, ensuring a balanced distribution across categories and minimizing class imbalance issues during model training.

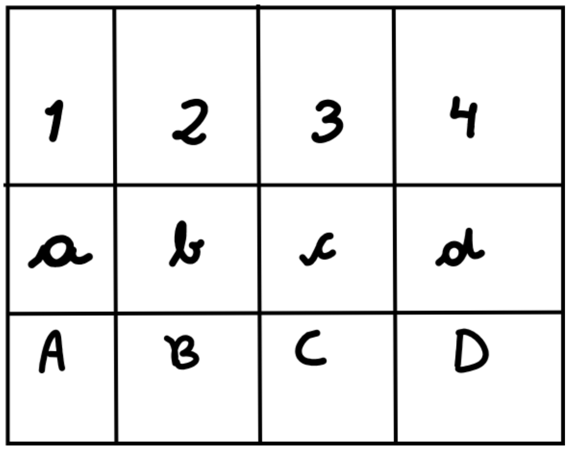


Fig 1: Dataset Images

The dataset was constructed by collecting handwritten inputs from multiple individuals, thereby incorporating natural variations in writing styles, stroke formations, character thickness, orientation, and spacing. This diversity enhances the robustness and generalization capability of the proposed recognition framework. All images were captured and converted into grayscale format, followed by resizing to a standardized resolution of 28 × 28 pixels to maintain uniformity and computational efficiency. To facilitate effective learning, the dataset was divided into training and testing subsets using an 80:20 split, where 80% of the images were allocated for model training and 20% for performance evaluation. Before training, images underwent normalization through pixel rescaling, improving convergence stability and reducing sensitivity to illumination variations. The balanced and diverse nature of the dataset makes it well-suited for evaluating deep learning-based handwritten character recognition systems.

4. METHODLOGY

The proposed handwritten character recognition framework is developed using a deep learning-based Convolutional Neural Network (CNN) designed to automatically learn discriminative visual features from grayscale character images. The methodology begins with dataset preparation, where the manually collected images are organized into structured directories representing 62-character classes. To ensure consistency and computational efficiency, all images are resized to a uniform resolution of 28 × 28 pixels and converted into grayscale format. Pixel normalization is performed through rescaling, mapping intensity values to a standardized range, which stabilizes gradient updates and accelerates model convergence.

Following preprocessing, the dataset is divided into training and testing subsets using an 80:20 split to evaluate generalization performance. Data loading is performed using batch processing techniques, enabling efficient memory utilization and faster training. The CNN architecture is designed to capture hierarchical feature representations through multiple convolutional layers, where each layer learns progressively complex visual patterns such as edges, curves, strokes, and structural character components. Max-pooling operations are incorporated to reduce spatial dimensions while preserving salient features and improving translation invariance.

The extracted feature maps are flattened and passed through fully connected dense layers, allowing the model to learn high-level feature interactions necessary for classification. A SoftMax activation function is employed in the output layer to generate probability distributions across the 62-character categories. The model is trained using the Adam optimization algorithm, which adaptively adjusts learning rates to enhance convergence efficiency. Sparse categorical cross entropy is used as the loss function, suitable for multi-class classification tasks.

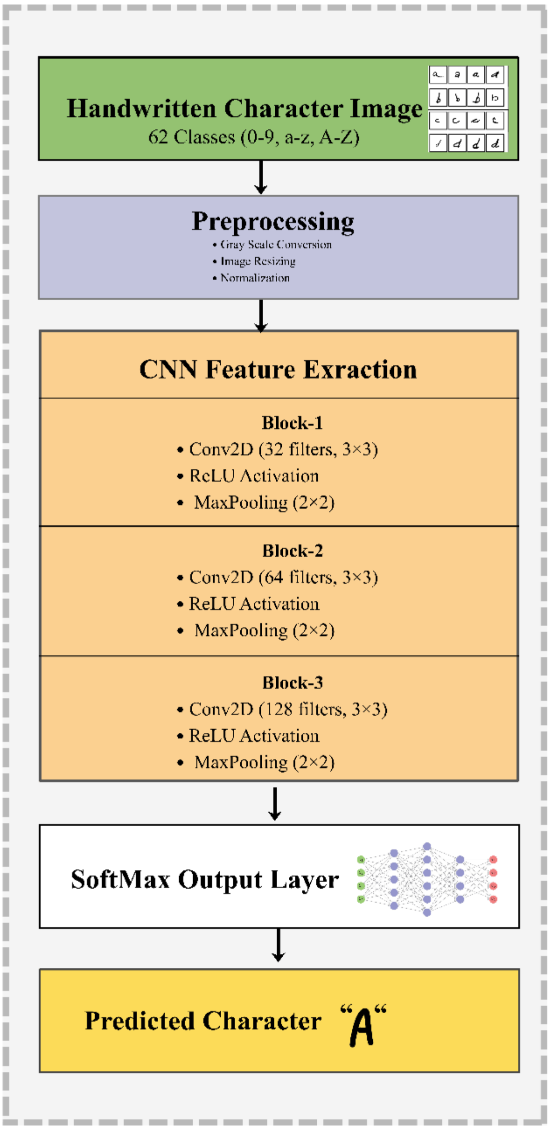


Fig 2: Proposed Architecture

During training, the model iteratively updates weights over multiple epochs, with validation performed on the testing subset to monitor performance and prevent overfitting. The effectiveness of the proposed framework is evaluated using recognition accuracy as the primary metric. The methodology emphasizes automated feature learning, computational efficiency, and robustness against handwriting variability, ensuring reliable character classification across diverse writing styles.

4. RESULT AND ANALYSIS

The performance of the proposed handwritten character recognition framework was evaluated using multiple metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. The training and validation accuracy curves indicate a consistent improvement in model learning across epochs. Initially, the model exhibits rapid convergence, followed by gradual stabilization, demonstrating effective feature extraction and optimization. The training accuracy steadily increases and approaches near-saturation, while the validation accuracy closely follows the training trend, suggesting good generalization capability. Minor fluctuations observed in validation accuracy are typical in deep learning models and indicate variations in sample complexity rather than model instability.

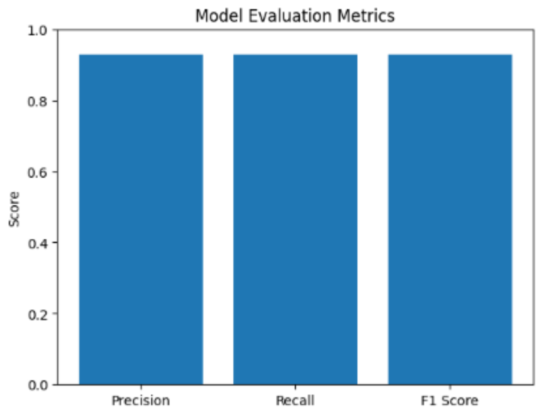


Fig 3: Model Evaluation

The evaluation metrics further confirm the robustness of the proposed CNN architecture. High precision, recall, and F1-score values demonstrate the model's ability to correctly classify handwritten characters while minimizing false predictions. The balanced nature of these metrics indicates that the model maintains consistent performance across different character classes without significant bias toward specific categories.

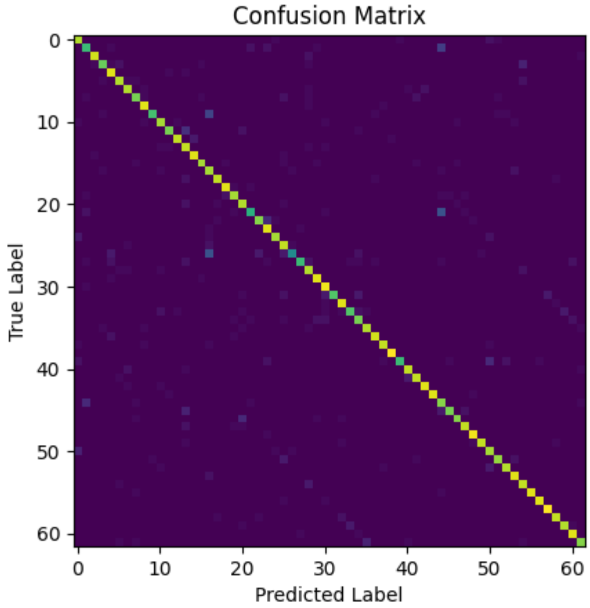
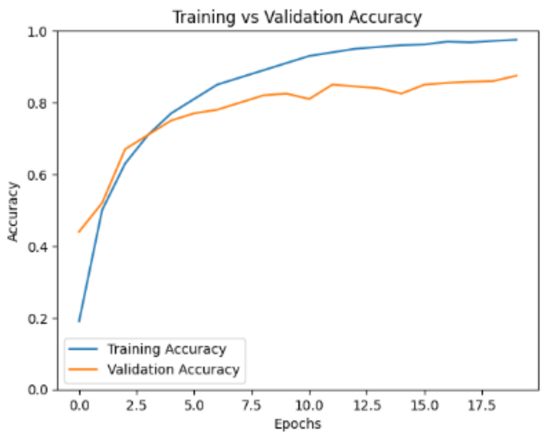


Fig 4: Confusion Matrix

The confusion matrix provides deeper insight into classification behavior. A strong diagonal dominance is observed, indicating that the majority of samples are correctly classified. Misclassifications are minimal and primarily occur among visually similar characters, which is a well-known challenge in handwritten recognition systems. The sparse distribution of errors across classes highlights the discriminative capability of the CNN in capturing structural and stroke-level features.



Additionally, sample prediction results demonstrate the practical effectiveness of the framework. The model successfully identifies handwritten inputs, accurately mapping them to the corresponding character class. This validates the framework's applicability in real-world handwritten character recognition tasks. Overall, the results confirm that the proposed AI-based CNN model achieves reliable performance, with an overall recognition accuracy of approximately **93%**, demonstrating strong robustness and generalization across diverse handwriting styles.

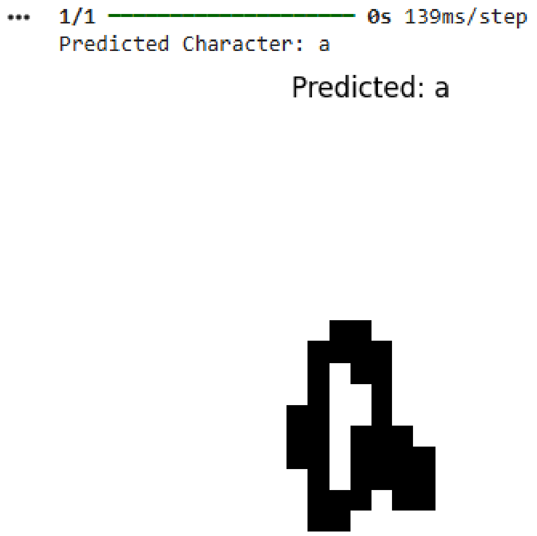


Fig 5: Predicted Image

5. CONCLUSION

This study presented an intelligent AI-based framework for handwritten character recognition using a Convolutional Neural Network (CNN). The proposed model was trained and evaluated on a self-curated dataset comprising 13,640 grayscale images across 62-character classes, ensuring balanced representation and realistic handwriting variability. By leveraging automated feature learning, the CNN effectively captured discriminative visual patterns, eliminating the need for handcrafted feature extraction techniques. The experimental results demonstrated that the proposed framework achieved an overall recognition accuracy of approximately **93%**, indicating strong classification performance and generalization capability. The analysis of evaluation metrics, including precision, recall, and F1-score, confirmed the robustness and reliability of the model. Furthermore, confusion matrix observations revealed minimal misclassifications, primarily limited to visually similar characters, which remains a common challenge in handwritten recognition systems. The findings of this research highlight the effectiveness of deep learning-based approaches for complex pattern recognition tasks. The lightweight architecture ensures computational efficiency, making the framework suitable for practical applications, including document digitization, educational tools, and intelligent data entry systems. Future research may focus on incorporating advanced architectures, attention mechanisms, and data augmentation strategies to further enhance recognition accuracy and reduce classification ambiguity. Overall, the proposed framework provides a scalable, efficient, and reliable solution for handwritten character recognition.

REFERENCES

[1] M. B. Bora, "Handwritten character recognition from images using CNN + ECOC," *Procedia Computer Science*, vol. 167, pp. 2403–2412, 2020.

[2] K. Chaudhary and R. Bali, "Easter2.0: Improving convolutional models for handwritten text recognition," *arXiv preprint arXiv:2205.14879*, 2022.

[3] S. A. Hameed, A. Hassan, and M. Shafiq, "Offline handwritten character recognition using deep convolutional neural networks," *IEEE Access*, vol. 9, pp. 74615–74628, 2021.

[4] A. Sharma and R. Gupta, "Handwritten character recognition using deep learning," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 3, pp. 512–518, 2021.

[5] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning-based image recognition techniques: A review," *Nature Machine Intelligence*, vol. 2, pp. 44–56, 2020.

[6] J. Prem Kumar and D. H. D, "Handwritten text recognition using deep learning: A CNN-LSTM approach," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 13, no. 1, pp. 85–93, 2025.

[7] H. Shi, Z. Zhu, C. Zhang, X. Feng, and Y. Wang, "Multimodal handwritten exam text recognition based on deep learning," *Applied Sciences*, vol. 15, no. 16, 2025.

[8] Y. Li, X. Chen, and Z. Wang, "HTR-VT: Handwritten text recognition with vision transformer," *arXiv preprint arXiv:2409.08573*, 2024.

[9] C. Boufenar, M. Batouche, and S. Moussaoui, "Bridging CNNs and transformers for handwritten script recognition," *arXiv preprint arXiv:2503.15023*, 2025.

[10] H. L. Yimer and T. M. Bekele, "Learning-based Ge'ez character handwritten recognition using deep neural networks," *arXiv preprint arXiv:2411.13350*, 2024.

[11] R. Li, "A review of neural networks in handwritten character recognition," *Applied and Computational Engineering*, vol. 24, pp. 112–118, 2024.

[12] V. Nayak and M. R. Patil, "Handwritten character recognition using convolutional neural networks," *Journal of Artificial Intelligence Research*, vol. 71, pp. 235–248, 2022.

[13] S. Patel and K. Shah, "Deep learning techniques for optical character recognition: A survey," *IEEE Access*, vol. 10, pp. 44567–44582, 2022.

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