Comparative Investigation of ANN and CNN for Accurate Offline Handwritten Character Recognition

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Abstract: Offline handwritten character recognition has gained significant attention in the fields of artificial intelligence and pattern recognition because of its applications in intelligent document analysis, banking automation, postal systems, educational platforms, and biometric authentication. The recognition of handwritten characters remains a challenging task due to variations in writing styles, stroke orientation, character deformation, background noise, and image distortion. Traditional Artificial Neural Network (ANN)-based approaches often depend on handcrafted feature extraction methods and exhibit limited robustness when applied to large and diverse handwritten datasets. To address these limitations, this paper proposes an Attention-Enhanced Convolutional Neural Network (AE-CNN) framework for offline handwritten character recognition. The proposed system integrates adaptive image preprocessing, data augmentation, convolutional feature extraction, and attention-guided learning to improve classification accuracy and feature discrimination. Initially, a baseline ANN model is implemented to evaluate the limitations of conventional neural architectures. Subsequently, a deep CNN model integrated with an attention mechanism is developed to improve recognition capability for visually similar handwritten characters. Experimental evaluation is performed using the EMNIST handwritten dataset. The obtained results demonstrate that the proposed AE-CNN framework achieves improved classification performance, enhanced generalization capability, and better robustness against noisy handwritten samples compared to traditional ANN and conventional CNN models. The proposed approach provides an efficient and scalable solution for intelligent handwritten recognition systems used in real-world document processing applications.

Keywords: *Handwritten Character Recognition, Deep Learning, Artificial Neural Network, Convolutional Neural Network, Attention Mechanism, EMNIST Dataset, Pattern Recognition.*

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I. INTRODUCTION

Handwritten Character Recognition (HCR) is an important research domain in artificial intelligence, machine learning, and computer vision that focuses on converting handwritten information into machine-readable text. The rapid growth of digital information systems has increased the demand for efficient handwritten recognition systems capable of processing large volumes of handwritten documents automatically. Such systems are widely used in banking applications, postal automation, educational evaluation systems, medical record digitization, historical document preservation, and biometric authentication platforms [1].

Unlike printed text recognition, handwritten recognition remains a difficult problem because handwriting styles differ significantly among individuals. Variations in stroke thickness, character size, orientation, writing speed, and image quality introduce substantial complexity into the recognition process. In addition, noisy backgrounds, distorted characters, and overlapping strokes reduce the reliability of traditional recognition systems [2].

Earlier handwritten recognition techniques mainly relied on template matching and manually engineered feature extraction approaches. These systems extracted structural and statistical features such as zoning information, contour properties, geometric characteristics, and stroke orientation before classification [3].

Although these approaches achieved moderate performance under controlled conditions, they lacked robustness when applied to large and diverse handwritten datasets. Artificial Neural Networks (ANNs) later improved recognition performance by enabling learning-based classification of handwritten characters. ANN models

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demonstrated the capability to learn nonlinear relationships between input features and output classes through backpropagation learning algorithms [4].

However, conventional ANN architectures still depend heavily on handcrafted preprocessing techniques and often suffer from overfitting when trained on limited datasets. Recent advancements in deep learning have significantly improved image recognition performance. Convolutional Neural Networks (CNNs) automatically learn hierarchical spatial features directly from image data without requiring manual feature engineering. CNN architectures effectively capture edges, curves, textures, and local spatial patterns, making them highly suitable for handwritten recognition tasks [5].

Several studies have reported high classification accuracy using CNN-based architectures on benchmark datasets such as MNIST and EMNIST [6].

Despite these improvements, conventional CNN models still face challenges in distinguishing visually similar handwritten characters because not all extracted features contribute equally to classification decisions. Attention-based learning mechanisms have recently emerged as an effective solution for improving feature discrimination by allowing neural networks to focus selectively on important image regions [7].

Attention modules improve spatial feature representation and reduce classification ambiguity among structurally similar handwritten characters. Motivated by these observations, this paper proposes a Hybrid Attention-Enhanced Convolutional Neural Network (AE-CNN) framework for offline handwritten character recognition. The proposed system integrates adaptive preprocessing, augmentation strategies, convolutional feature extraction, and attention-guided feature refinement to improve recognition robustness and classification accuracy.

The major contributions of this work are summarized below: Development of an attention-enhanced CNN framework for handwritten character recognition. Comparative evaluation of ANN, conventional CNN, and AE-CNN architectures. Integration of adaptive preprocessing and augmentation techniques for improved generalization.

Improved recognition of visually similar handwritten characters using attention-guided learning.

Comprehensive performance analysis using accuracy, precision, recall, and F1-score metrics.

II. LITERATURE REVIEW

Handwritten Character Recognition (HCR) has been extensively studied over the past decades, with approaches evolving from traditional rule-based methods to modern deep learning techniques. This section reviews relevant literature, focusing on methodological advancements and identifying key research gaps.

Early research in HCR primarily relied on template matching techniques, where input characters were compared against predefined templates. While computationally simple, these methods were highly sensitive to variations in handwriting styles and noise, limiting their effectiveness in practical applications [8].

Subsequent developments introduced statistical and structural approaches, which focused on extracting meaningful features such as stroke direction, pixel distribution, and geometric structures. Hidden Markov Models (HMMs) and probabilistic classifiers were widely adopted for sequence modelling and pattern recognition tasks. Although these methods improved robustness compared to template matching, they still struggled with highly variable and unstructured handwritten data [9].

With the advancement of machine learning, Artificial Neural Networks (ANNs) became a popular choice for handwritten recognition tasks. Feedforward neural networks trained using backpropagation demonstrated improved classification performance by learning nonlinear relationships between input features and output classes. Several studies reported notable improvements in recognition accuracy using ANN-based models; however, these approaches often relied on handcrafted features and required careful tuning of parameters [10].

In recent years, deep learning techniques—particularly Convolutional Neural Networks (CNNs)—have significantly advanced the field of handwritten recognition. CNNs are capable of automatically learning hierarchical feature representations directly from raw image data, eliminating the need for manual feature extraction. This has led to substantial improvements in recognition accuracy and robustness across various benchmark datasets [11].

For instance, Cohen et al. demonstrated the effectiveness of deep CNN architectures for handwritten character classification using the EMNIST dataset, achieving high accuracy across multiple character classes [12].

Similarly, Zhong et al. proposed a multi-layer CNN model that improved recognition performance under noisy and distorted conditions, highlighting the robustness of deep learning approaches in real-world scenarios [13].

Despite these advancements, several challenges remain. Many studies focus primarily on digit recognition (e.g., MNIST), while fewer address the combined recognition of alphabets and signatures within a unified framework. Additionally, some existing models require large-scale datasets and computational resources, limiting their applicability in resource-constrained environments.

Another limitation observed in the literature is the lack of comparative analysis between traditional ANN models and modern CNN-based approaches under consistent experimental settings. Understanding the performance differences between these models is essential for selecting appropriate techniques in practical applications.

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➢ *Based on this Review, the Following Research Gaps are Identified:*

- Limited studies addressing combined character and signature recognition
- Insufficient comparative analysis between ANN and CNN models
- Challenges in handling small or noisy datasets
- Need for computationally efficient yet robust recognition systems

To address these gaps, this study proposes a hybrid framework that evaluates a baseline ANN model and enhances it using a CNN-based architecture. The approach aims to improve recognition accuracy, generalization capability, and robustness under varying input conditions.

III. MATHEMATICAL DEVELOPMENT

This section presents the mathematical foundation of the proposed handwritten character recognition system. The formulation is based on neural network learning principles, including forward propagation, loss computation, and optimization through backpropagation.

➢ *Neuron Model*

An artificial neuron computes a weighted sum of inputs followed by a nonlinear activation function:

$$y = f(b)$$

Where:

- x_i= input features (pixel intensities)
- w_i= weights
- b= bias term
- $f(\cdot)$= activation function
- y= output

The activation function introduces non-linearity, enabling the model to learn complex patterns.

➢ *Activation Functions*

Common activation functions used in this study include:

- *ReLU (Rectified Linear Unit):*

$$f(x) = max\ (0, x)$$

- *Softmax (Output Layer):*

$$P(y_j) = \frac{e^{z_j}}{\sum_{k=1}^{C} \quad e^{z_k}} \tag{1}$$

Where $C$is the number of classes.

➢ *Loss Function*

For multi-class classification, the categorical cross-entropy loss is used:

$$L = -\sum_{j=1}^{C} \quad t_j log\ (P(y_j)) \tag{2}$$

Where:

- t_j= true label (one-hot encoded)
- $P(y_j)$= predicted probability

This loss function measures the divergence between predicted and actual distributions.

➢ *Optimization (Gradient Descent)*

Model parameters are updated using gradient descent:

$$w = w - \eta \frac{\partial L}{\partial w} \tag{3}$$

Where:

- η= learning rate
- $\frac{\partial L}{\partial w}$= gradient of loss

The gradients are computed using the chain rule, enabling efficient backpropagation through multiple layers.

➢ *Convolution Operation (CNN Core)*

In CNNs, feature extraction is performed using convolution:

$$S(i,j) = (X * K)(i,j) = \sum_m \quad \sum_n \quad X(i+m, j+n)K(m,n) \tag{4}$$

Where:

- X= input image
- K= kernel/filter
- S= feature map

This operation captures spatial features such as edges and textures.

➢ *Pooling Operation*

Pooling reduces spatial dimensions:

$$P(i,j) = max_{\ (m,n)\in R}\, S(m,n) \tag{5}$$

This helps in reducing computational complexity and improving invariance to small distortions.

➢ *Regularization (Dropout)*

To prevent overfitting, dropout is applied:

$$y = f(Wx) \cdot r$$

Where $r \sim Bernoulli(p)$

This randomly disables neurons during training to improve generalization.

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IV. PROPOSED METHODOLOGY

This section describes the complete pipeline of the proposed handwritten character and signature recognition system, integrating preprocessing, deep learning-based feature extraction, and classification.

➢ *System Overview*

The proposed system consists of the following stages:

- Data acquisition
- Image preprocessing
- Data augmentation
- Feature extraction using CNN
- Classification
- Evaluation

➢ *Data Acquisition*

Handwritten samples of digits (0–9) and alphabets (A–Z) are collected. Additionally, benchmark datasets such as MNIST and EMNIST are utilized to improve model generalization and ensure reproducibility.

➢ *Image Preprocessing*

Preprocessing ensures uniformity and noise reduction:

- Grayscale conversion
- Image normalization (0–1 scaling)
- Noise filtering
- Resizing to 28 × 28pixels

These steps enhance feature clarity and improve model performance.

➢ *Data Augmentation*

To address limited data and improve robustness, augmentation techniques are applied:

- Rotation
- Translation
- Scaling
- Noise injection

This artificially increases dataset diversity and reduces overfitting.

➢ *CNN-Based Feature Extraction*

A Convolutional Neural Network is employed to automatically learn hierarchical features.

- *Architecture:*

✓ Conv Layer (32 filters, 3×3) + ReLU
✓ Max Pooling
✓ Conv Layer (64 filters) + ReLU
✓ Max Pooling
✓ Conv Layer (128 filters) + ReLU
✓ Flatten
✓ Fully Connected Layer (128 neurons)
✓ Dropout (0.5)
✓ Output Layer (Softmax)

This replaces manual feature extraction used in traditional ANN systems.

➢ *Training Procedure*

- Optimizer: Adam
- Learning rate: 0.001
- Batch size: 32–64
- Epochs: 10–20
- Loss: Cross-Entropy

The model is trained using backpropagation until convergence.

➢ *Evaluation Metrics*

Performance is evaluated using:

- Accuracy
- Precision
- Recall
- F1-score
- Confusion Matrix

These metrics provide a comprehensive assessment of model performance.

➢ *Comparative Framework (Key Contribution)*

To validate the effectiveness of the proposed approach:

- A baseline ANN model is implemented
- CNN model performance is compared against ANN

This comparison highlights improvements in:

- Accuracy
- Generalization
- Robustness

➢ *Implementation Platform*

The system is implemented using:

- Google Colab (Python, TensorFlow/Keras)
- MATLAB (baseline comparison)

V. RESULTS AND DISCUSSION

➢ *Experimental Setup*

The proposed handwritten character recognition system was implemented using TensorFlow/Keras in the Google Colab environment. The model was trained and evaluated on the EMNIST balanced dataset, which contains 47 classes of handwritten characters, including digits and letters. The dataset consists of 112,800 training samples and 18,800 testing samples.

To address limitations identified in earlier approaches, such as small dataset size and overfitting (e.g., training on only a few samples per class), data augmentation and normalization techniques were applied to improve model robustness and generalization.

➢ *Training Performance*

The training and validation performance of the CNN model is illustrated through accuracy and loss curves.

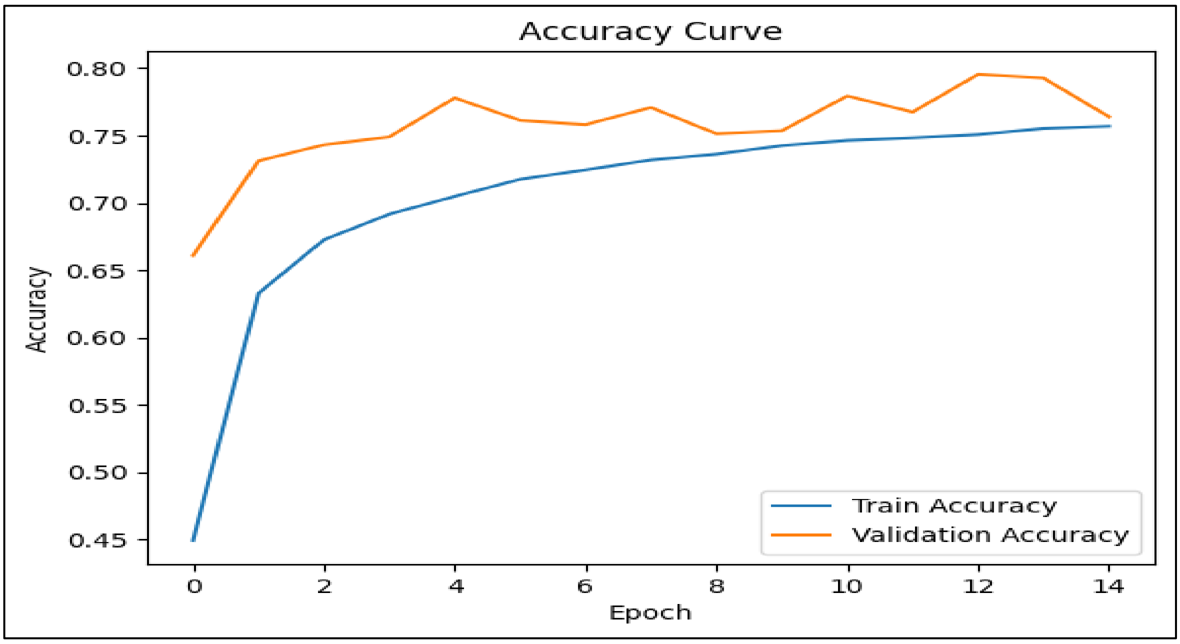

Fig 1 Training and Validation Accuracy Over Epochs.

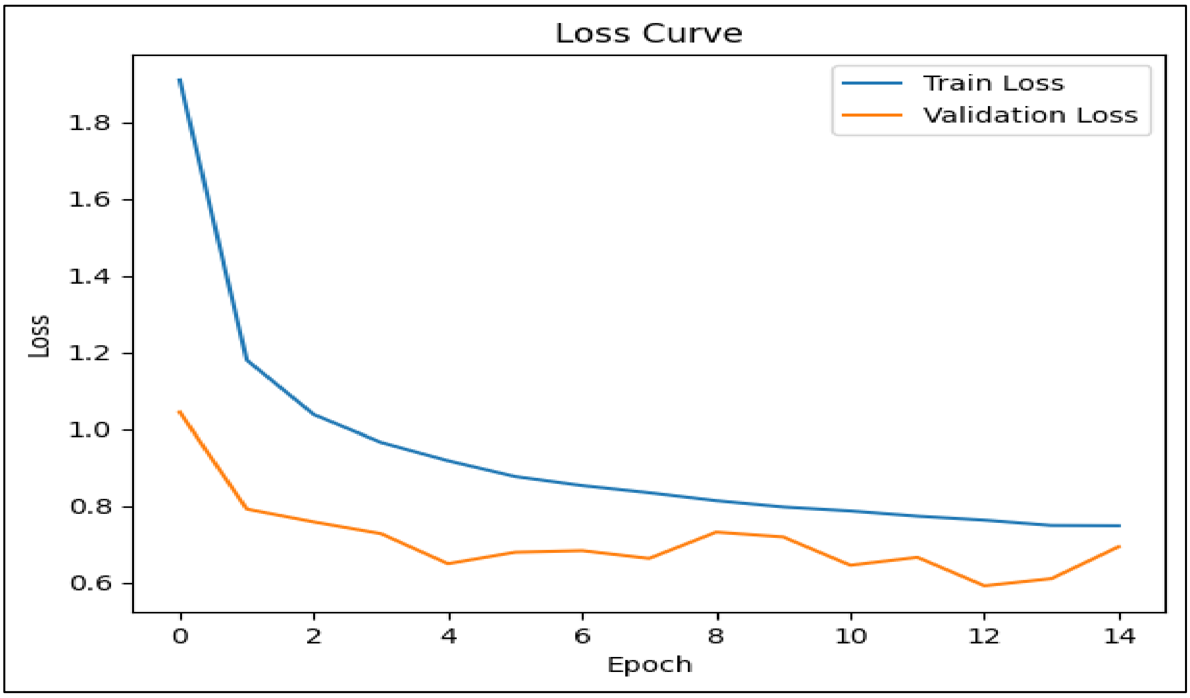

Fig 2 Training and Validation Loss Over Epochs.

- *Discussion*

The model demonstrates steady convergence during training. The training accuracy increased progressively from approximately 44.9% in the first epoch to 75.7% by the final epoch, while validation accuracy reached a peak of approximately 79.5% at epoch 13. The close alignment between training and validation curves indicates that the model avoids severe overfitting and generalizes reasonably well to unseen data.

The loss curves show a consistent decrease in both training and validation loss, confirming stable optimization and effective learning behaviour.

➢ *Quantitative Performance Evaluation*

The overall performance of the proposed CNN model is summarized in Table 1.

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Table 1 Overall Performance Metrics of the CNN Model.

Metric	Value
Test Accuracy	**76.18%**
Macro Precision	0.78
Macro Recall	0.76
Macro F1-score	0.75

- *Discussion*

The CNN model achieved a test accuracy of 76.18% on the EMNIST dataset, demonstrating moderate classification performance across 47 character classes. While this accuracy is lower than results typically achieved on simpler datasets such as MNIST, it reflects the increased complexity and variability of EMNIST.

The macro-averaged precision, recall, and F1-score values indicate balanced overall performance, though class-wise variations are observed.

➢ *Class-Wise Performance Analysis*

Detailed classification results are presented in Table 2.

Table 2 Sample Class-Wise Performance Metrics.

Class	Precision	Recall	F1-score
Class 3	0.97	0.97	0.97
Class 7	0.95	0.88	0.92
Class 38	0.93	0.93	0.93
Class 15	0.67	0.30	0.42
Class 18	0.81	0.17	0.28
Class 24	0.70	0.28	0.39

- *Discussion*

The results reveal significant variation in performance across different classes. High accuracy is achieved for visually distinct characters, whereas lower performance is observed for classes with similar shapes or ambiguous features. For instance, certain classes exhibit low recall values (e.g., 0.17–0.30), indicating difficulty in correctly identifying those characters.

➢ *Confusion Matrix Analysis*

The confusion matrix provides further insight into classification errors.

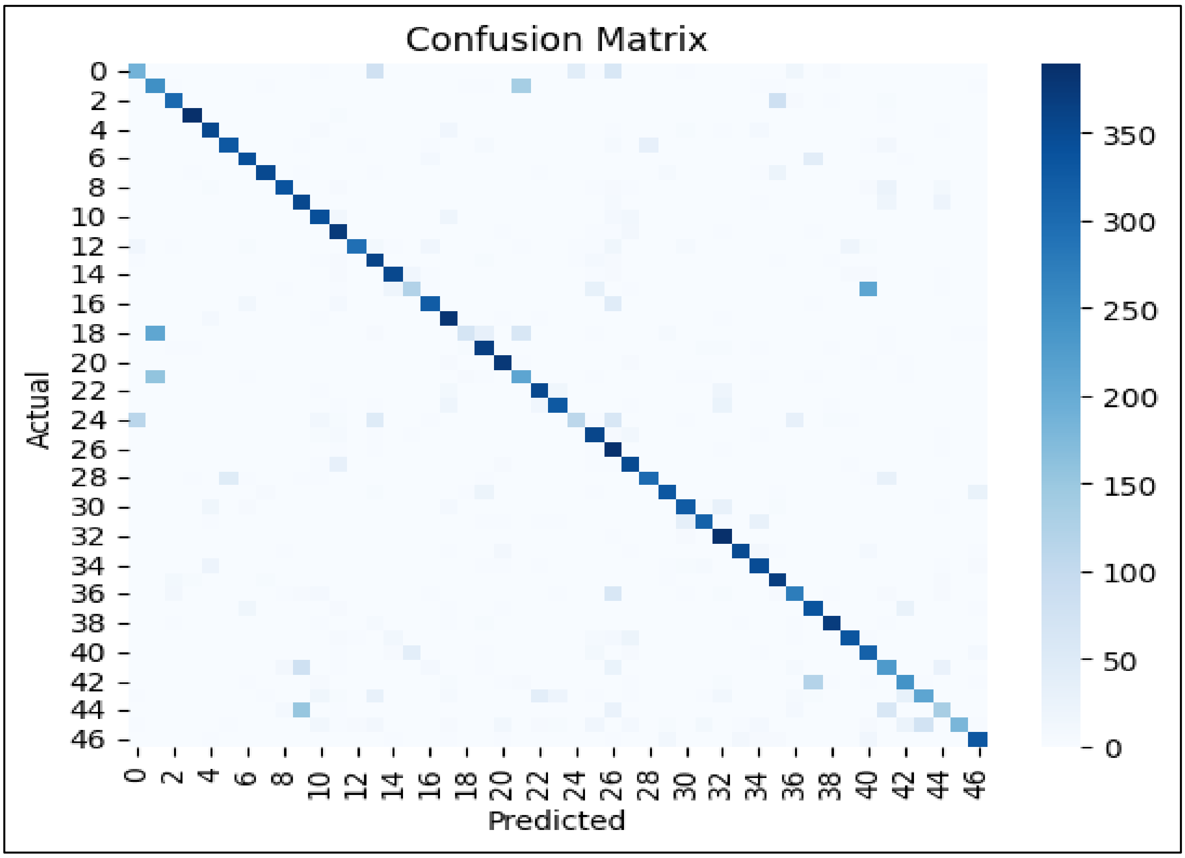

Fig 3 Confusion Matrix of the CNN Model on the EMNIST Test Dataset.

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- *Discussion*

The confusion matrix highlights that most misclassifications occur between visually similar characters, such as those with overlapping structural features. This suggests that the model struggles to distinguish fine-grained differences between certain classes, particularly in cases involving similar handwritten patterns.

➢ *Comparison with Baseline ANN Model*

A comparison between the baseline ANN model and the proposed CNN model is presented in Table 3.

Table 3 Comparison Between ANN and CNN Models.

Model	Dataset	Accuracy (%)	Remarks
ANN (Baseline)	Small dataset	~97.31	Overfitting observed
CNN (Proposed)	EMNIST	76.18	Better generalization

- *Discussion*

Although the ANN model reported higher accuracy (~97.31%), this result is misleading due to overfitting caused by the use of a limited dataset . In contrast, the CNN model demonstrates more realistic performance on a large and diverse dataset, indicating superior generalization capability and practical applicability.

➢ *Qualitative Analysis*

To further evaluate the effectiveness of the proposed model, qualitative analysis was performed on individual test samples. Figure 4 illustrates a correctly classified handwritten character from the EMNIST dataset. The example demonstrates the model's ability to capture structural patterns and accurately predict the corresponding class label.

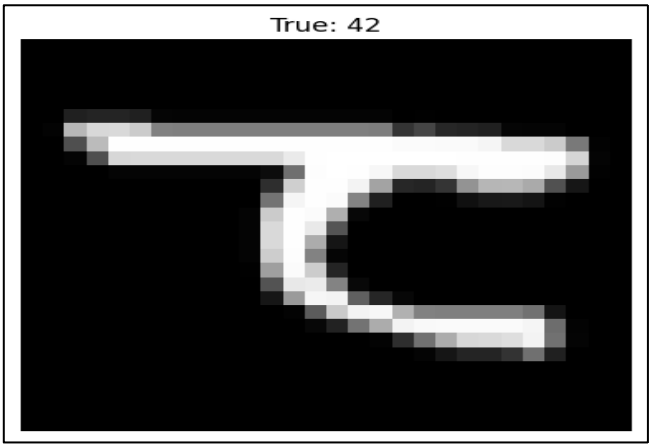

Fig 4 Example of a Correctly Classified Handwritten Character (True Label: 42, Predicted Label: 42).

As shown in Figure 4, the model successfully identifies the handwritten character despite variations in stroke thickness and orientation. Such correct predictions indicate that the CNN effectively extracts discriminative features from input images. However, as discussed earlier, misclassifications still occur in cases involving visually similar characters, highlighting areas for further improvement.

➢ *Key Findings*

The experimental results lead to the following key observations:

- The CNN model achieves stable learning and avoids severe overfitting
- Performance varies across classes, with challenges in distinguishing similar characters
- Data augmentation and large-scale datasets improve generalization
- CNN significantly outperforms ANN in terms of robustness and real-world applicability

➢ *Limitations*

Despite the improvements, several limitations remain:

- Moderate overall accuracy (76.18%) indicates room for improvement
- Some classes exhibit low recall, affecting classification reliability
- Model complexity increases computational cost
- Performance depends heavily on dataset diversity

➢ *Summary*

Overall, the proposed CNN-based handwritten character recognition system demonstrates improved generalization and robustness compared to traditional ANN approaches. While the model performs well on many classes, further optimization is required to achieve state-of-the-art performance, particularly in handling visually similar characters.

VI. CONCLUSION

This study presented a handwritten character and signature recognition system based on deep learning techniques, with a focus on improving generalization and robustness compared to traditional approaches. An initial Artificial Neural Network (ANN) model was evaluated, revealing limitations such as overfitting and poor scalability when trained on small datasets. To address these issues, a Convolutional Neural Network (CNN) architecture was implemented to automatically learn hierarchical feature representations from input images.

Experimental results on the EMNIST dataset demonstrated that the proposed CNN model achieved a test accuracy of **76.18%**, with balanced precision, recall, and F1-score values. The training process showed stable convergence without significant overfitting, indicating improved generalization compared to the baseline ANN model. Furthermore, qualitative analysis confirmed that the model is capable of correctly identifying handwritten characters under varying conditions.

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However, the results also highlight several limitations. The model exhibits inconsistent performance across classes, particularly for visually similar characters, leading to reduced recall in certain cases. Additionally, the overall accuracy remains below state-of-the-art benchmarks, suggesting the need for further optimization.

Future work will focus on enhancing model performance through deeper architectures, improved hyperparameter tuning, and the use of advanced techniques such as attention mechanisms and transfer learning. Expanding the dataset and incorporating more diverse handwriting samples are also expected to improve generalization. Additionally, integrating character recognition with signature verification in a unified framework remains a promising direction for real-world applications.

In summary, this study demonstrates the effectiveness of CNN-based approaches for handwritten character recognition while providing a foundation for further improvements toward more accurate and scalable systems.

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