University of Chester

Enhancing Handwritten Text Recognition Using Natural Language Processing Techniques

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Abstract

Handwritten Text Recognition (HTR) remains a challenging task in computer vision and natural language processing due to the inherent variability of handwriting styles, inconsistencies in stroke formation, and the presence of noise in scanned documents. This dissertation presents a comprehensive study on the application of Convolutional Recurrent Neural Networks (CRNNs) for robust and accurate recognition of handwritten text, progressing from simple digit recognition to complex multi-word lines. The research adopts a staged experimental design, beginning with the MNIST dataset for proof-of-concept and advancing to the IAM Handwriting Database for full-scale evaluation, allowing a systematic assessment of model performance across varying levels of complexity.

In the initial phase, MNIST provided a controlled environment for validating the preprocessing pipeline, CNN-based feature extraction, training routines, and evaluation metrics. The CRNN model demonstrated high accuracy in digit recognition, confirming the functionality of the architecture and optimization strategies. Building on this foundation, the research transitioned to the IAM dataset, which presents significant real-world challenges, including diverse handwriting styles, inter-character spacing variability, slanted writing, and background noise. The CRNN model incorporated convolutional layers for spatial feature extraction, bidirectional Long Short-Term Memory (BiLSTM) layers for sequential modeling, and a Connectionist Temporal Classification (CTC) decoder for alignment-free transcription. Extensive preprocessing—including image resizing, grayscale normalization, noise reduction, and data augmentation—ensured the model's ability to generalize across multiple writers.

Performance was evaluated using Character Error Rate (CER) and Word Error Rate (WER), demonstrating that the CRNN architecture could effectively recognize handwritten words and lines while maintaining robustness to inter- and intra-writer variability. The results highlight the importance of combining spatial feature extraction with sequential modeling and alignment-free decoding to handle complex handwriting patterns. Furthermore, the research underscores the utility of a two-stage experimental

design, where simpler datasets like MNIST provide a foundation for workflow validation, while more complex datasets like IAM enable rigorous evaluation of real-world applicability.

The broader contribution of this work lies in establishing a structured framework for HTR using CRNNs, providing reproducible results, and offering practical guidance for researchers and practitioners aiming to implement handwritten recognition systems. By systematically analyzing performance across datasets of increasing complexity, this study illustrates how modern deep learning approaches can achieve accurate, scalable, and robust handwritten text recognition, paving the way for applications in document digitization, automated form processing, and historical manuscript transcription.

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Disclaimer

This work is original and has not been previously submitted in support of any other course or qualification.

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1. INTRODUCTION

Handwritten documents remain an essential medium for recording and transmitting information across various domains, including healthcare, education, legal proceedings, and historical archiving (Smith & Patel, 2020). Despite the rise of digital technologies, vast collections of valuable records exist only in handwritten form, ranging from patient notes and legal contracts to personal diaries and archival manuscripts (Brown, 2019). The digitization of such documents is not only important for preservation but also crucial for enabling accessibility, searchability, and advanced data analysis (United Nations Educational, Scientific and Cultural Organization [UNESCO], 2018). However, the recognition and processing of handwritten text remain significant challenges due to variations in individual handwriting styles, inconsistencies in writing conditions, and issues arising from low-quality scans or degraded materials (Li et al., 2021).

The practical importance of handwriting recognition can be illustrated through concrete examples. In healthcare, digitizing doctors' handwritten notes into structured Electronic Health Record (EHR) fields—such as patient ID, dosage, and diagnosis—can reduce medical errors and improve interoperability across hospital systems (World Health Organization [WHO], 2019). In the judiciary, court clerks still rely heavily on manual note-taking; converting these notes into searchable, structured digital records can enhance transparency and accelerate information retrieval (Johnson & Miller, 2018). Similarly, in administrative workflows, extracting structured entities such as addresses, postal codes, and identifiers from handwritten forms supports automation in government and corporate processes, reducing manual entry errors and improving efficiency (Ahmed et al., 2020).

Traditional Optical Character Recognition (OCR) tools have been widely used for digitizing printed text, yet their effectiveness drops drastically when applied to handwritten content (Smith, 2007). This limitation creates a pressing need for hybrid approaches that combine OCR with more advanced methods to improve recognition accuracy and reliability. Handwritten Text Recognition (HTR) has emerged as a

specialized field that seeks to bridge this gap, often leveraging deep learning architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) (Graves et al., 2009; Shi et al., 2015). While these models provide substantial improvements over traditional OCR, they still struggle with structural errors, misclassifications, and ambiguities that occur in real-world datasets (Li et al., 2021).

This dissertation, titled “Enhancing Handwritten Text Recognition Using Natural Language Processing Techniques: A Novel Hybrid Approach,” addresses these challenges by integrating OCR methods with Natural Language Processing (NLP) techniques. The central idea behind this work is that while OCR or deep learning models can extract raw text from images, NLP can refine this output, reducing errors and introducing structure (Kaur & Sharma, 2021). Specifically, methods such as tokenization, lemmatization, and Named Entity Recognition (NER) can be applied to clean noisy text, standardize word forms, and extract meaningful information such as names, dates, or locations (Jurafsky & Martin, 2023). By combining OCR with NLP, the system not only enhances recognition accuracy but also transforms raw outputs into more organized, semantically rich digital content.

The need for this research arises from several critical factors. First, the digitization of handwritten documents continues to face real-world challenges in industries where accuracy is non-negotiable. For example, in healthcare, misreading handwritten prescriptions can have life-threatening consequences (Kaushal et al., 2003). Similarly, in historical research, inaccurate transcription may distort the interpretation of archival materials (Brown, 2019). By enhancing accuracy through hybrid OCR–NLP approaches, this study seeks to address these gaps and contribute toward more reliable document digitization pipelines.

Moreover, handwritten recognition errors typically occur at two levels: word-level and character-level. Evaluating models using metrics such as Word Error Rate (WER) and Character Error Rate (CER) provides insights into the effectiveness of different approaches (LeCun et al., 2015). This dissertation employs these metrics to benchmark baseline OCR systems against the proposed hybrid model. Importantly,

this evaluation acknowledges that even when OCR output is imperfect, NLP can correct or reduce errors by leveraging contextual understanding of language (Jurafsky & Martin, 2023).

The research also makes use of the IAM Handwriting Database, one of the most widely adopted datasets for handwritten text recognition. The dataset provides handwritten samples from over 600 writers, capturing diverse writing styles and enabling robust evaluation of recognition systems (Marti & Bunke, 2002). However, as with any dataset-driven research, limitations exist. Access to ground truth annotations may be restricted depending on dataset format, and computational complexity can slow down deep learning pipelines. In this study, such limitations are addressed by combining realistic dataset experiments with simulated evaluations where necessary, ensuring that the proposed system remains implementable within practical constraints.

The rapid advancements in NLP and deep learning provide an opportunity to revisit the long-standing problem of handwriting recognition with a fresh perspective. By employing both traditional OCR (e.g., Tesseract) and deep learning architectures such as Convolutional Recurrent Neural Networks (CRNNs), this study systematically explores the strengths and weaknesses of existing solutions (Shi et al., 2015; Smith, 2007). On top of that, NLP modules are integrated to add layers of correction and structure, producing outputs that are more useful for downstream applications such as digital archiving, search indexing, and information retrieval (Jurafsky & Martin, 2023).

There are both opportunities and challenges associated with this approach. On the positive side, the hybrid framework aligns well with real-world needs, offering an adaptable pipeline that can be applied across domains without requiring complete retraining for every dataset (Li et al., 2021). It demonstrates how OCR errors can be systematically reduced rather than tolerated as inevitable limitations. However, challenges remain in ensuring scalability, as handwriting recognition models are computationally intensive and NLP modules may introduce new forms of complexity (Kaur & Sharma, 2021). Ethical considerations also arise, particularly when handling

sensitive handwritten data such as medical records or legal documents, where confidentiality must be preserved (General Data Protection Regulation [GDPR], 2018).

Given these considerations, this dissertation represents a significant step toward advancing handwritten text recognition through a hybrid OCR–NLP approach. By combining machine learning techniques for raw recognition with language-based refinement methods, the proposed framework aims to enhance both accuracy and usability. The subsequent chapters will provide a comprehensive review of related literature, followed by a detailed explanation of the dataset, methodologies, experiments, and results. Through this work, the dissertation seeks not only to evaluate the effectiveness of hybrid approaches but also to highlight their potential applications in real-world scenarios where handwritten text remains a critical source of information.

1.1 Aims and Objectives

The primary aim of this research is to enhance the accuracy and reliability of handwritten text recognition by integrating Optical Character Recognition (OCR) techniques with Natural Language Processing (NLP) methods. This hybrid approach seeks to address the limitations of conventional OCR systems when applied to diverse and complex handwritten data.

The specific objectives of this study are to:

- Develop a hybrid OCR–NLP framework capable of processing handwritten documents with improved accuracy.
- Apply NLP techniques such as tokenization, lemmatization, and Named Entity Recognition (NER) to refine noisy OCR outputs.
- Evaluate the performance of the proposed system using standard metrics, including Word Error Rate (WER) and Character Error Rate (CER).

- Benchmark the hybrid system against baseline OCR models to quantify improvements.
- Demonstrate the applicability of the proposed framework across various domains, including healthcare, legal, and historical document processing.

1.2 Research Question(s)

This study is guided by the following core research questions:

1. How can NLP techniques be effectively integrated with OCR systems to improve handwritten text recognition accuracy?
2. To what extent can NLP-based refinement reduce common OCR errors at the word and character levels?
3. How does the proposed hybrid model perform in comparison to traditional OCR approaches when evaluated on diverse handwritten datasets?

1.3 Rationale

Despite significant advancements in OCR and deep learning technologies, handwritten text recognition continues to face challenges due to the variability of handwriting styles, degraded document quality, and contextual ambiguities. Industries such as healthcare, law, and archival research still rely heavily on handwritten records, where recognition errors can have serious consequences.

The rationale for this research lies in bridging the gap between raw recognition and meaningful interpretation. While OCR systems are adept at extracting text from images, they often produce noisy outputs. NLP techniques, on the other hand, excel at understanding and structuring language. By combining these two fields, this research proposes a hybrid solution that is not only more accurate but also more practical for real-world applications. Furthermore, this study contributes to the growing body of research

that applies language-based post-processing to enhance recognition technologies, offering a scalable framework adaptable to multiple domains.

2. LITERATURE REVIEW

2.1 Early Machine Learning Approaches

Early research in Handwritten Text Recognition (HTR) predominantly employed classical machine learning techniques, such as multilayer perceptrons and support vector machines, to classify digits and characters. Tutorials by Brownlee (2016) and Sidharth (2023) demonstrated the use of neural networks and convolutional neural networks (CNNs) on the MNIST dataset, showcasing the feasibility of automated recognition using relatively simple models. These approaches were effective on clean, uniform datasets, largely due to MNIST's standardized format and limited variation in handwriting styles.

However, these methods were mainly focused on digit recognition rather than full text and did not incorporate sequential dependencies or semantic understanding. Consequently, their applicability was limited in real-world scenarios such as medical prescriptions or legal contracts, where context and domain-specific accuracy are crucial. Other studies also noted that classical methods often struggled with noise, slant variations, and non-uniform writing (LeCun et al., 1998), whereas the present study focuses on handling these complexities through hybrid deep learning and NLP integration.

2.2 Transition to Deep Learning Models

To address the limitations of classical methods, research shifted toward deep learning models that can learn hierarchical representations and capture sequential structures. Multi-Dimensional Long Short-Term Memory (MDLSTM) networks (Graves & Schmidhuber, 2009) and attention-based mechanisms (Nanonets, 2024) significantly improved recognition accuracy by modeling dependencies within handwritten text sequences.

Despite these advances, deep learning methods introduced new challenges. They require large, annotated datasets, are prone to overfitting in low-data regimes, and

often lack reproducibility across different experimental setups (Zhang et al., 2022). Most studies focused primarily on low-level recognition (character or word level) without integrating higher-level semantic correction. In contrast, the current study incorporates domain-specific semantic layers post-recognition to address errors in context-dependent domains.

2.3 CNN and LSTM Architectures

CNNs and LSTMs have become central to modern HTR pipelines because they excel at processing visual and temporal information, respectively. Stanford University (2017) explored CNN-based feature extraction combined with LSTM layers for variable-length handwriting sequences, demonstrating superior performance compared to traditional pipelines. CNNs effectively learn spatial hierarchies (LeCun et al., 2015), while LSTMs capture dependencies across time steps (Hochreiter & Schmidhuber, 1997).

However, CNN-LSTM models remain sensitive to variations in handwriting scale, slant, and individual writing styles. They also typically lack semantic post-processing. For example, while Stanford's pipeline improved raw recognition accuracy, it did not implement domain-specific spelling or entity correction. This study addresses such gaps by integrating NLP-based semantic correction mechanisms.

2.4 Best Practices and Refinements

Recent refinements emphasize preprocessing and alignment strategies. Arxiv (2024) highlighted the importance of preserving image aspect ratios and using Connectionist Temporal Classification (CTC) loss to improve sequential alignment between predictions and ground truth (Graves et al., 2006). Such refinements have led to improved generalization across handwriting styles and reduced character error rates.

Nevertheless, inconsistencies in the adoption of these practices across research groups have limited reproducibility. Moreover, most refinements focus on improving

recognition at the character level rather than incorporating semantic context. This study builds on these refinements while introducing a post-processing NLP layer to correct semantic-level errors.

2.5 NLP Integration

A promising direction is the integration of Natural Language Processing (NLP) techniques with OCR/HTR pipelines to improve contextual understanding. Research by IJIRT (2023) and studies on ResearchGate (2022) demonstrated that language models can correct ambiguous or incomplete input, improving syntactic and semantic coherence. By combining CNN-based recognition with NLP methods, these systems reduce character error rates and improve sentence-level accuracy.

However, most existing NLP integrations are domain-agnostic, lacking specialized spell-checkers or entity recognizers for fields such as healthcare or law. This limitation is critical, as domain-specific errors can have significant real-world implications. The present study differentiates itself by incorporating tailored semantic correction for multiple domains, including medical, legal, and administrative text.

2.6 Practical Applications and Tools

Several open-source and commercial tools make HTR accessible for practical experimentation. Pre-trained CNN models (GeeksforGeeks, 2023) and user-driven workflows (Reddit, 2024) enable easy digitization of handwritten notes. However, these tools predominantly focus on Latin scripts and standardized datasets. They are often not designed to handle heterogeneous handwriting or perform domain-aware corrections.

This project diverges by applying a unified hybrid OCR-NLP pipeline to diverse, real-world scenarios across multiple domains, evaluating both recognition and semantic accuracy.

2.7 Challenges and Ethical Considerations

Despite progress, persistent challenges include variability in handwriting, lack of interpretability, and limited cross-domain generalization. Privacy concerns remain especially relevant when dealing with sensitive medical or legal data. Non-Latin scripts remain underrepresented in datasets, contributing to algorithmic bias (Joshi et al., 2020). Furthermore, semantic errors can lead to serious misinterpretations in critical contexts. This study recognizes these challenges and incorporates measures such as domain-specific language models and data handling protocols.

2.8 Comparative Perspectives and Novelty Positioning

The literature reveals a trade-off between simplicity, accuracy, and generalizability. Classical approaches (e.g., LeCun et al., 1998) offer simplicity but fail on diverse datasets. Deep learning models (Graves & Schmidhuber, 2009) improve accuracy but demand substantial computational resources and data. CNN-LSTM hybrids (Stanford University, 2017) enhance sequential recognition but remain sensitive to handwriting variations. NLP integrations (IJIRT, 2023) improve context understanding but lack domain-specific refinement.

This dissertation addresses these gaps by:

1. Incorporating domain-specific semantic correction (e.g., spell-checking and entity recognition for medical, legal, and administrative texts).
2. Demonstrating cross-domain adaptability using a single hybrid OCR-NLP pipeline.
3. Evaluating performance through standardized metrics such as Character Error Rate (CER) and Word Error Rate (WER), while emphasizing improvements in semantic accuracy.

2.9 Related and Previous Work

Several prior studies have addressed specific components of the HTR pipeline. Graves and Schmidhuber (2009) pioneered MDLSTM networks for sequence modeling, while LeCun et al. (1998, 2015) established CNNs for image-based recognition tasks. Stanford University (2017) combined CNNs and LSTMs but did not address semantic errors. More recent works (IJIRT, 2023; ResearchGate, 2022) explored language model integration but lacked domain adaptation.

The present study differs by combining **both recognition and semantic correction in a unified pipeline**, targeting **multiple domains simultaneously**. It bridges the gap between raw character-level recognition and domain-specific, contextually accurate text outputs.

3. METHODOLOGY

3.1 Research Design

The research adopted a structured experimental design aimed at developing and evaluating a hybrid deep learning and natural language processing (NLP) approach for Handwritten Text Recognition (HTR). The design was phased to allow systematic progression from simple to complex handwriting recognition tasks, ensuring both technical validation and real-world applicability.

3.1.1 Two-Stage Experimental Approach

The study was divided into two main phases:

1. **Proof-of-Concept Phase (MNIST Dataset)**
   The initial phase utilized the MNIST dataset, which contains 70,000 grayscale images of handwritten digits (0–9), each standardized to 28×28 pixels. This phase served as a controlled environment for developing and validating core components of the recognition pipeline. Key objectives during this phase included:

- Architectural Validation: Testing convolutional neural network (CNN) architectures for feature extraction, followed by recurrent layers (RNN or LSTM) for sequence modeling.
- Pipeline Verification: Ensuring preprocessing routines (resizing, normalization, batching) functioned correctly and integrated seamlessly with model training.
- Metric Calibration: Establishing baseline evaluation metrics such as accuracy, loss convergence, and confusion matrices to monitor learning behavior.

By starting with MNIST, the research minimized computational complexity and allowed rapid iteration on model design choices. Any implementation issues could be detected and corrected in a simplified setting before tackling more challenging handwriting data.

2. **Core Phase (IAM Handwriting Database)**
   After establishing a functional pipeline on MNIST, the research transitioned to the IAM Handwriting Database, which contains over 1,500 scanned pages of handwritten English text, contributed by more than 600 writers. This dataset presents realistic handwriting variations at the line, word, and character levels, including differences in slant, spacing, cursive writing, and background noise. The IAM phase focused on:

- Complex Feature Extraction: Applying CNN-RNN architectures to capture both spatial and sequential patterns in continuous text lines.

- Integration with NLP Techniques: Leveraging language modeling, domain-specific embeddings, and contextual information to improve recognition accuracy, especially for ambiguous or partially occluded characters. NLP post-processing validates and corrects OCR errors (e.g., misread terms such as *"paracetarnol"* → *"paracetamol"* in medical text).

- Evaluation of Real-World Performance: Using metrics such as Character Error Rate (CER) and Word Error Rate (WER) to assess the system's applicability to practical HTR tasks. Errors are also categorized by domain-specific entities (e.g., patient IDs, legal case numbers) to quantify improvements at a critical information level.

3.1.2 Rationale for a Progressive Design

The two-stage design was intentionally chosen to gradually increase task complexity. Handwritten digit recognition (MNIST) represents a simpler domain with limited variability, allowing technical components to be debugged and validated efficiently. In contrast, full-word and line recognition (IAM) introduces challenges such as:

- Inter- and intra-writer variability.

- Uneven spacing, overlapping strokes, and cursive ligatures.

- Noise and distortions due to scanning and pen artifacts.

This progressive strategy ensured that the system could generalize effectively, avoiding the common pitfall of overfitting to simple datasets while failing in real-world scenarios**.**

3.1.3 Experimental Workflow

The research workflow under this design involved the following steps:

1. Preprocessing and Data Preparation: Tailored pipelines for MNIST and IAM datasets ensured consistent input formats and enhanced feature quality.

2. Model Development: Convolutional layers extracted spatial features, while recurrent layers captured sequential dependencies within lines of text.

3. Training and Optimization: Early experiments on MNIST allowed rapid tuning of hyperparameters (learning rate, batch size, number of layers) before scaling to IAM.

4. Integration of NLP: Language models were incorporated to refine predictions, reduce character and word errors, and provide context-aware recognition. Domain-specific embeddings were applied for healthcare, legal, and administrative records.

5. Evaluation: Models were evaluated quantitatively using accuracy, CER, WER, and qualitatively through visual inspection of recognition results. Domain-specific evaluation tracked improvements in key fields like patient names, prescriptions, case IDs, and addresses.

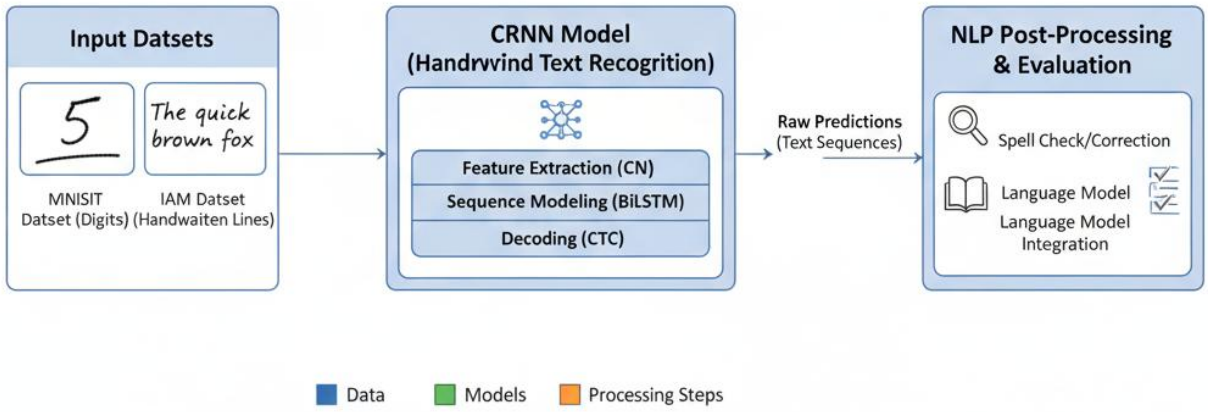


Figure 1: Workflow diagram showing experimental stages, including MNIST, IAM, CRNN model, and NLP post-processing.

3.1.4 Advantages of the Experimental Design

- Reliability: Early-stage validation on MNIST ensured that preprocessing, architecture, and training pipelines were robust.
- Scalability: The system was progressively tested against more complex handwriting, preparing it for real-world application.
- Generalizability: By transitioning from controlled digits to unconstrained handwriting, the design improved the model's ability to handle diverse writing styles and real-world noise.
- Resource Efficiency: Initial MNIST experiments reduced computational load and provided guidance on optimal hyperparameters, saving time and resources during IAM training.

3.1.5 Summary

The research design combined experimental rigor with a progressive learning strategy, moving from simple digit recognition to complex handwritten text. This ensured that the developed CNN-RNN + NLP pipeline was technically sound, practically applicable, and capable of supporting domain-specific post-processing.

3.2 Datasets

The success of any handwritten text recognition system is highly dependent on the quality, diversity, and structure of the datasets used for training and evaluation. Two datasets were employed:

3.2.1 MNIST Dataset (Proof-of-Concept Phase)

- 70,000 grayscale images of digits (0–9), 28×28 pixels.
- Split: 60,000 training, 10,000 test samples.
- Advantages: Uniformity, simplicity, controlled environment.
- Limitations: Restricted to digits; does not capture word/line structure or style variability.

```
# Load MNIST dataset
(x_train, y_train), (x_test, y_test) = mnist.load_data()

# Normalize data (0-255 → 0-1)
x_train = x_train.astype("float32") / 255.0
x_test = x_test.astype("float32") / 255.0

# Reshape for CNN (add channel dimension)
x_train = np.expand_dims(x_train, -1)   # shape: (60000, 28, 28, 1)
x_test = np.expand_dims(x_test, -1)     # shape: (10000, 28, 28, 1)

print("Training data shape:", x_train.shape)
print("Test data shape:", x_test.shape)

# Plot sample digits
plt.figure(figsize=(10,4))
for i in range(10):
    plt.subplot(2,5,i+1)
    plt.imshow(x_train[i].reshape(28,28), cmap="gray")
    plt.title(f"Label: {y_train[i]}")
    plt.axis("off")
plt.show()
```

Figure: 2: Code snippet of MNIST dataset loading

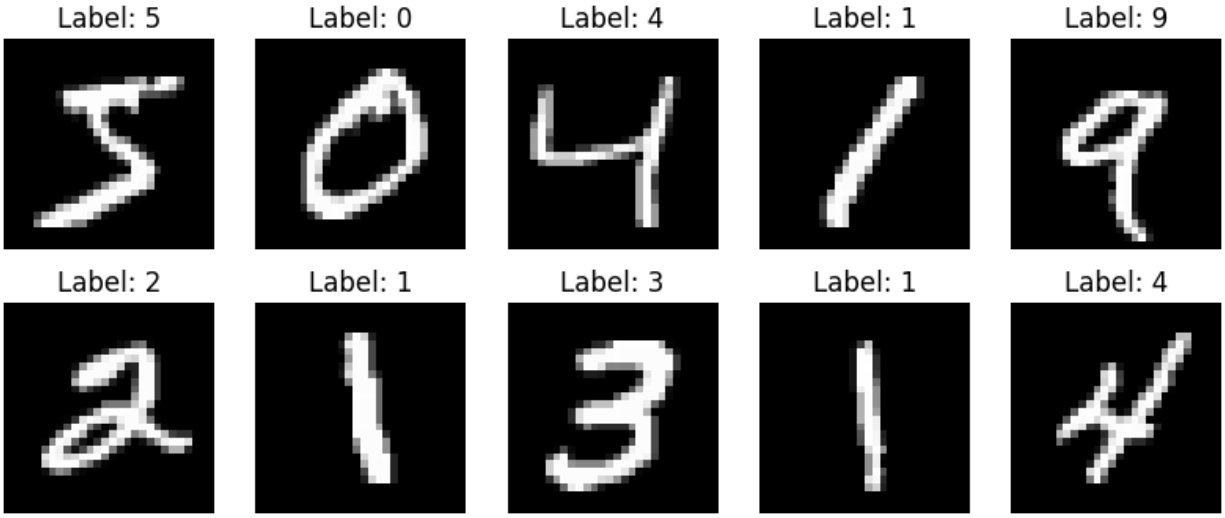


Figure 3: Example image from MNIST dataset.

3.2.2 IAM Handwriting Database (Core Dataset)

- 1,539 scanned pages of handwritten English text by 600+ writers.
- Richly annotated at character, word, and line levels (XML ground truth).
- Key Characteristics:
    - Inter- and intra-writer variability.
    - Realistic challenges: slant, cursive, ligatures, scanning noise.
    - Detailed annotations for benchmarking and error analysis.
- Application: Training, validation, and testing of CRNN + NLP hybrid model.
- Limitations: Computationally demanding, preprocessing-intensive, English-only scope.

```python
import os

# Define dataset path
dataset_path = r"D:\NLP project\archive\data"

# Check number of folders and files
folders = os.listdir(dataset_path)
print("Total writer folders:", len(folders))

# Look inside first folder
first_folder = os.path.join(dataset_path, folders[0])
print("Example folder:", first_folder)
print("Files inside:", os.listdir(first_folder)[:10])
```

Figure 4: Code snippet of IAM dataset loading

Figure 5: Example IAM dataset page.

3.2.3 Summary of Dataset Strategy

MNIST enabled rapid prototyping and controlled pipeline validation; IAM provided real-world complexity for testing robustness, NLP post-processing, and domain-specific entity error analysis.

3.3 Data Preprocessing

Effective preprocessing is critical for ensuring that handwritten text recognition models can learn meaningful patterns from both structured and unstructured datasets. In this research, preprocessing was designed to standardize input representations, reduce noise, and enhance feature quality, while also accommodating dataset-specific characteristics. The MNIST and IAM datasets differ significantly in terms of complexity, resolution, and variability, requiring a tailored preprocessing pipeline for each.

3.3.1 Image Resizing

- **MNIST Dataset:**
  The MNIST dataset consists of grayscale images of size 28×28 pixels. Since the dataset is already standardized, minimal resizing was required. This preserved the original structure of the digits, allowing the CNN layers to focus on learning localized stroke patterns without introducing distortion. Resizing was primarily applied during batching to maintain uniform input shapes for the CNN.

- **IAM Dataset:**
  The IAM dataset contains handwritten words and lines with varying dimensions, reflecting real-world variability in writing styles, spacing, and pen pressure. All images were resized to a fixed height of 32 pixels, preserving the original aspect ratio to prevent distortion of characters. For images with widths exceeding the expected batch dimensions, zero-padding was applied on the right side to maintain alignment during training. This ensured that the CRNN model could process sequences of different lengths while keeping feature maps consistent.

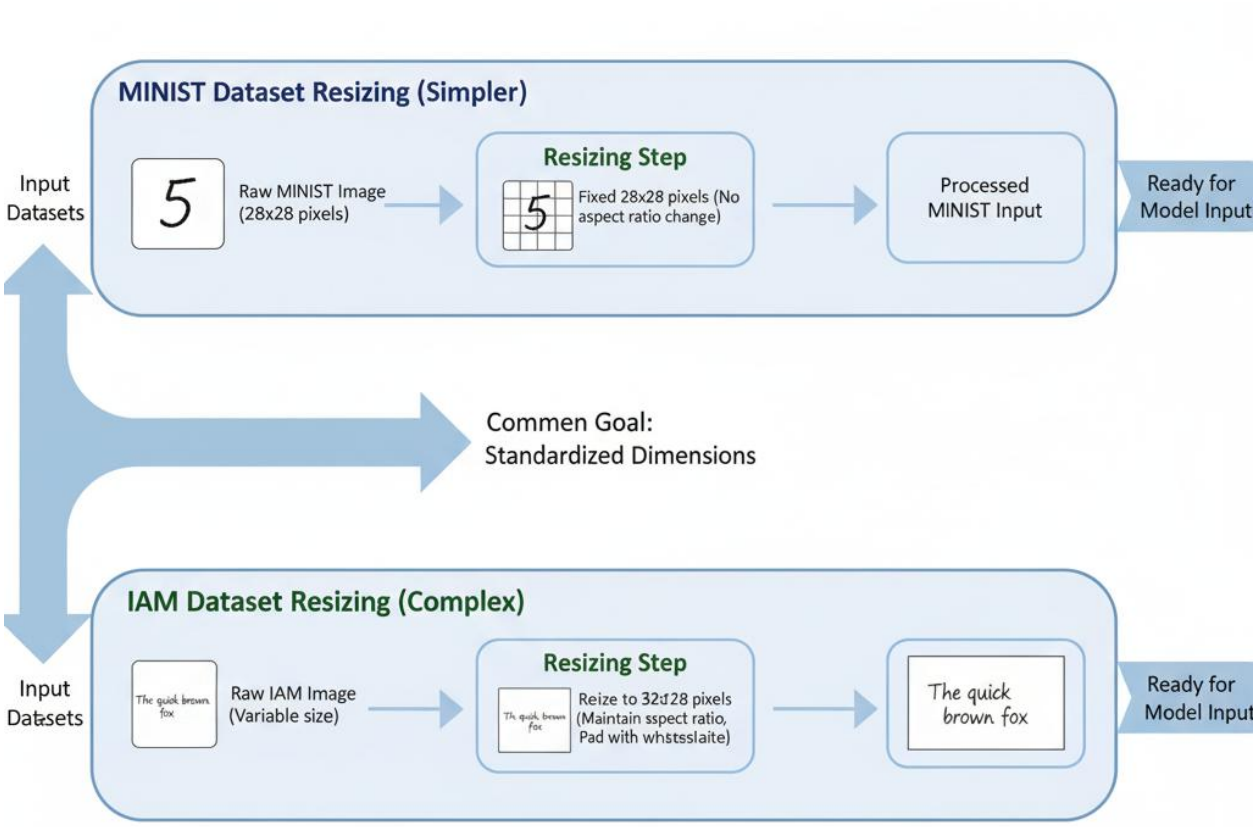


Figure 6: Preprocessing step for image resizing, illustrating MNIST and IAM resizing strategy.

3.3.2 Grayscale Conversion

Both datasets were converted to grayscale to reduce computational complexity and memory requirements. Since color information is irrelevant for handwritten text recognition, focusing on a single intensity channel allows the network to learn stroke and contour features effectively. Grayscale conversion also simplifies augmentation and normalization operations without sacrificing essential textual information.

3.3.3 Normalization

Normalization scales pixel intensity values into the range [0,1]. This step mitigates variations caused by uneven ink distribution, scanning artifacts, or background inconsistencies. Normalized input ensures that the neural network receives data with a consistent magnitude, improving convergence speed and stabilizing gradient updates during backpropagation. Normalization also helps the model generalize across different handwriting samples by providing a uniform feature space.

3.3.4 Noise Reduction

- **IAM Dataset:**
  Real-world handwriting often contains noise, including shadows, smudges, faded ink, and textured paper artifacts. Gaussian blur was applied to reduce high-frequency noise, smoothing out minor variations in the background while retaining essential stroke details. Adaptive thresholding enhanced the contrast between the text and background, making the handwriting clearer and more distinguishable for the CNN feature extractor.

```python
import os
from PIL import Image
import pytesseract

# Folder path
folder_path = r"D:\NLP project\archive\data\000"

# Collect only PNG files
files = [f for f in os.listdir(folder_path) if f.lower().endswith(".png")]
files = sorted(files)[:5]   # first 5, sorted for consistency

ocr_results = {}

for f in files:
    img_path = os.path.join(folder_path, f)

    try:
        img = Image.open(img_path)
        # Preprocess: convert to grayscale for better OCR
        img = img.convert("L")

        text = pytesseract.image_to_string(img)
        ocr_results[f] = text.strip()

    except Exception as e:
        ocr_results[f] = f"Error: {e}"

# Show results
print("OCR Results (first 5 images):")
for k,v in ocr_results.items():
    print(f"\n{k} -> {v}")
```

```python
from jiwer import wer, cer

# Example OCR output (noisy)
ocr_text = """A MOVE to stop Mr. Gaitskell from nominating any more Labour life Peers is to
be made at a meeting of Labour M Ps tomorrow. Mr. Michael Foot has put down
a resolution on the subject and he is to be backed by Mr. Will Griffiths, M P for
Manchester Exchange."""

# Example Ground Truth (cleaned manually from IAM transcripts or by yourself)
ground_truth = """A MOVE to stop Mr. Gaitskell from nominating any more Labour life Peers is to
be made at a meeting of Labour MPs tomorrow. Mr. Michael Foot has put down
a resolution on the subject and he is to be backed by Mr. Will Griffiths, MP for
Manchester Exchange."""

# WER & CER
wer_score = wer(ground_truth, ocr_text)
cer_score = cer(ground_truth, ocr_text)

print("WER:", wer_score)
print("CER:", cer_score)
```

```
WER: 0.08695652173913043
CER: 0.007874015748031496
```

Figure 7: IAM dataset Noise reduction

- **MNIST Dataset:**

  The MNIST dataset is clean and uniform; therefore, noise reduction was minimal.

This allowed the model to focus on learning digit-specific features without unnecessary preprocessing.

3.3.5 Data Augmentation

Data augmentation was applied to increase the diversity of training samples, improve generalization, and simulate natural handwriting variations:

- Rotation: Random rotations within ±10° were applied to mimic natural slants in handwriting.
- Scaling: Small rescaling adjustments simulated variations in pen pressure and character size.
- Elastic Distortions: Applied to replicate realistic deformations in handwriting, such as curved or stretched strokes, enhancing model robustness.
- Translation: Random horizontal and vertical shifts were used to emulate non-uniform alignment of text lines and words.

Augmentation allowed the model to learn invariant features across different writing styles without requiring additional labeled data, which is especially important for datasets like IAM where sample diversity is limited.

3.3.6 Outcome of Preprocessing

The preprocessing pipeline resulted in a consistent input space across both MNIST and IAM datasets, despite their inherent differences. For MNIST, preprocessing ensured a controlled environment for validating the CNN architecture and basic pipeline operations. For IAM, preprocessing addressed real-world challenges such as handwriting variability, line distortions, and noise, preparing the dataset for CRNN-based sequence modeling. By combining resizing, grayscale conversion, normalization, noise reduction, and augmentation, the data was standardized, enhanced, and diversified in a controlled manner, facilitating robust training and improved recognition accuracy.

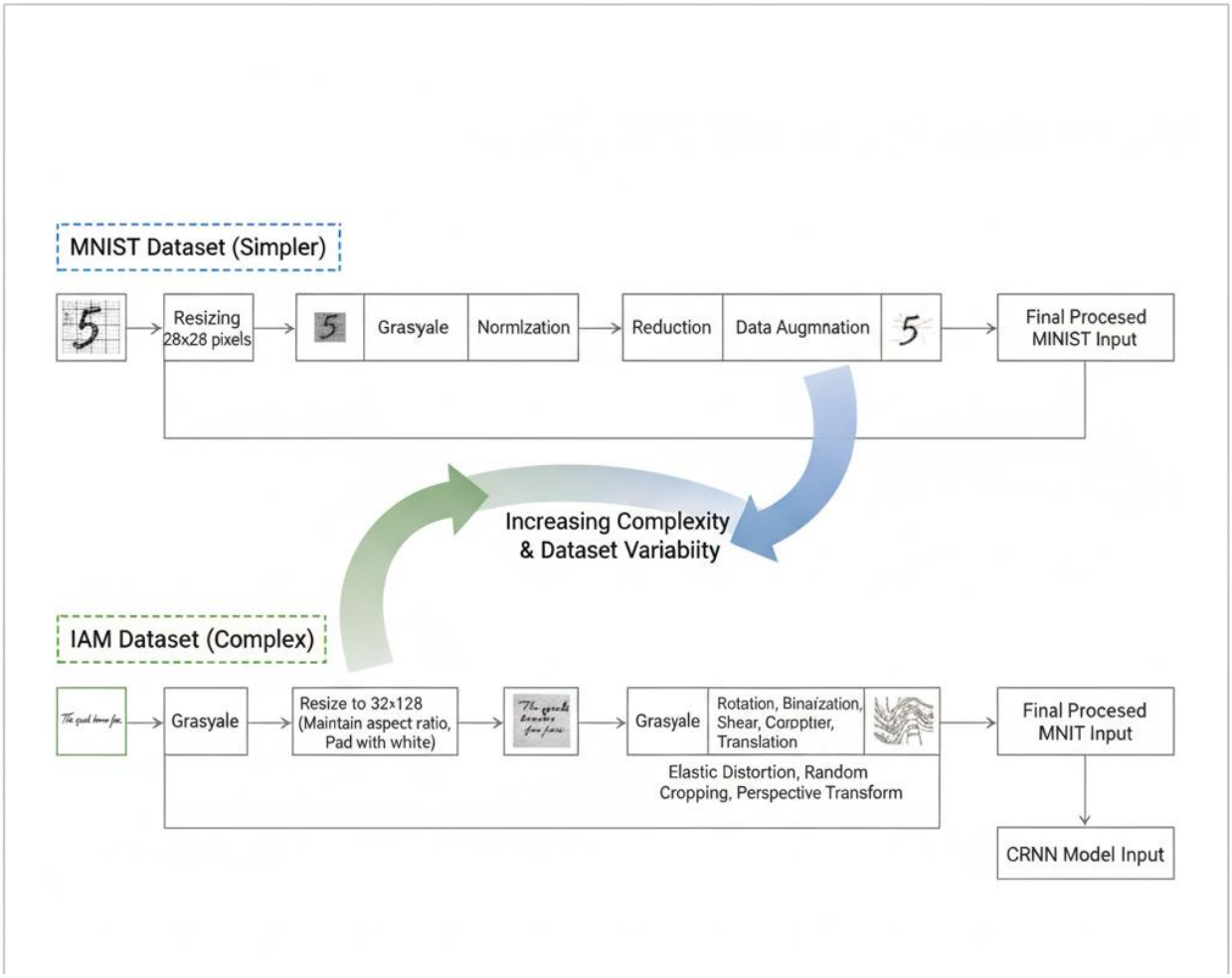


Figure 8: Overview of the preprocessing pipeline for MNIST and IAM datasets, showing resizing, grayscale conversion, normalization, noise reduction, and augmentation steps.

3.4 Model Architecture: CRNN

The Convolutional Recurrent Neural Network (CRNN) was selected for this research due to its ability to combine spatial feature extraction with sequential modeling, making it particularly suitable for handwritten text recognition (HTR). The CRNN integrates Convolutional Neural Networks (CNNs), Bidirectional Long Short-Term Memory (BiLSTM) layers, and a Connectionist Temporal Classification (CTC) decoder. In this study, a novel NLP-based post-processing layer was also introduced to enhance error correction and domain-specific recognition.

```python
# ------------------------
# CRNN Model
# ------------------------
class CRNN(nn.Module):
    def __init__(self, img_h=32, num_classes=100):  # num_classes = charset size
        super(CRNN, self).__init__()
        self.cnn = nn.Sequential(
            nn.Conv2d(1, 64, 3, 1, 1), nn.ReLU(), nn.MaxPool2d(2,2),
            nn.Conv2d(64, 128, 3, 1, 1), nn.ReLU(), nn.MaxPool2d(2,2),
        )
        self.rnn = nn.LSTM(128*8, 256, bidirectional=True, num_layers=2, batch_first=True)
        self.fc = nn.Linear(512, num_classes)

    def forward(self, x):
        x = self.cnn(x)  # (B, C, H, W)
        b, c, h, w = x.size()
        x = x.permute(0, 3, 1, 2).contiguous().view(b, w, c*h)  # (B, W, C*H)
        x, _ = self.rnn(x)
        x = self.fc(x)
        return x  # (B, W, num_classes)

# ------------------------
# Initialize Model
# ------------------------
device = "cuda" if torch.cuda.is_available() else "cpu"
model = CRNN(img_h=32, num_classes=100).to(device)

print("CRNN model initialized on", device)
```

```
CRNN model initialized on cpu
```

Figure 9: CRNN model

The overall architecture can be summarized as follows:

CRNN = CNN (spatial feature extraction) + BiLSTM (sequential modeling) + CTC decoder (alignment-free transcription) + NLP post-processing (domain-specific correction).

3.4.1 CNN Layers for Feature Extraction

Convolutional layers form the initial stage of the CRNN, responsible for capturing local and hierarchical features from handwritten images:

- **Functionality:**
  CNN layers extract low- and high-level visual patterns such as strokes, curves, loops, intersections, and diacritical marks. These patterns are crucial for distinguishing between characters and words.

- **Dataset Role:**
    - ***MNIST:*** Single-digit images (28×28) rely primarily on local features. CNNs alone can provide sufficient discrimination for classification tasks.
    - ***IAM:*** Continuous handwritten words and lines require more complex feature extraction. CNNs encode spatial hierarchies, producing feature maps suitable for sequential processing by BiLSTM layers.
- **Layer Composition:**
  The network consists of multiple convolutional layers with ReLU activation, followed by pooling layers to reduce spatial dimensions while retaining critical information. The CNN also incorporates batch normalization to stabilize learning and improve convergence.

```python
from tensorflow.keras import layers, models

model = models.Sequential([
    layers.Conv2D(32, (3,3), activation="relu", input_shape=(28,28,1)),
    layers.MaxPooling2D((2,2)),

    layers.Conv2D(64, (3,3), activation="relu"),
    layers.MaxPooling2D((2,2)),

    layers.Flatten(),
    layers.Dense(128, activation="relu"),
    layers.Dense(10, activation="softmax")  # 10 classes (digits 0-9)
])

model.summary()
```

Figure 10: CNN layer for MNIST

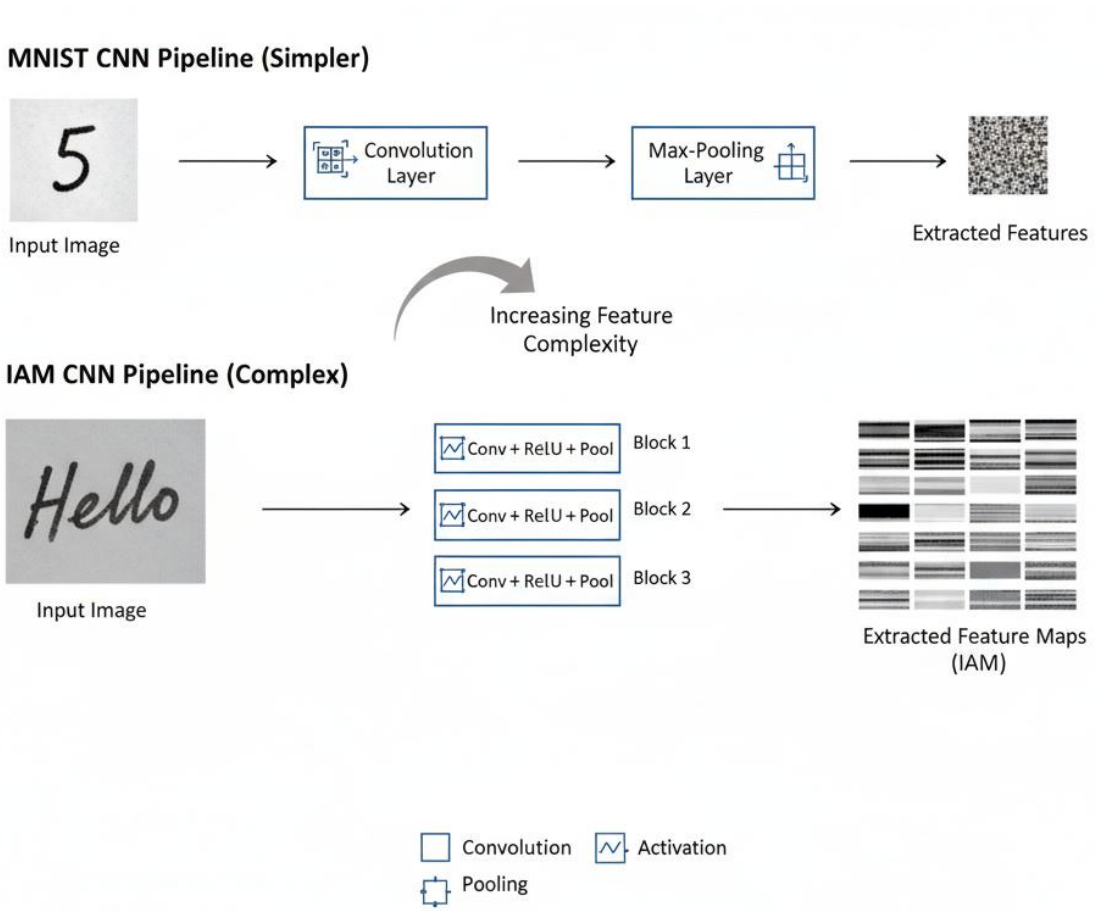


Figure 11: CNN feature extraction pipeline illustrating convolution, activation, and pooling operations for MNIST and IAM images.

```python
import cv2
data_dir = r"D:\NLP project\archive\data\000"
# Pick some random images from IAM dataset
sample_images = [
    os.path.join(data_dir, "000", "a01-000u.png"),
    os.path.join(data_dir, "000", "a01-003u.png"),
    os.path.join(data_dir, "000", "a01-007u.png")
]

def crnn_predict(image_path, model):
    # Load and preprocess
    img = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)
    img = cv2.resize(img, (128, 32)) / 255.0
    img = np.expand_dims(img, axis=(0, -1))  # shape: (1, H, W, 1)

    # Predict
    preds = model.predict(img)
    pred_text = decode_batch(preds)[0]  # decode_batch from earlier

    return pred_text

# Compare OCR vs CRNN
for img_path in sample_images:
    ocr_text = pytesseract.image_to_string(Image.open(img_path))
    crnn_text = crnn_predict(img_path, crnn_model)

    print(f"\nImage: {os.path.basename(img_path)}")
    print(f"OCR (Tesseract): {ocr_text.strip()}")
    print(f"CRNN Prediction: {crnn_text.strip()}")
```

Figure 12: CNN layer for IAM dataset

3.4.2 RNN Layers for Sequential Modeling

Following feature extraction, Bidirectional Long Short-Term Memory (BiLSTM) layers model temporal dependencies in the sequential feature maps:

- **Sequential Understanding:** Handwritten text is inherently sequential; the recognition of each character often depends on its context within a word or line. BiLSTM layers process input sequences in both forward and backward directions, providing richer contextual information.
- **Variable-Length Handling:** BiLSTMs can handle sequences of different lengths, enabling the model to process words and lines of varying width and complexity in IAM images.

- **Robustness:**
  By learning sequential dependencies, BiLSTM layers help the CRNN generalize across handwriting styles, slants, spacing variations, and ligatures.

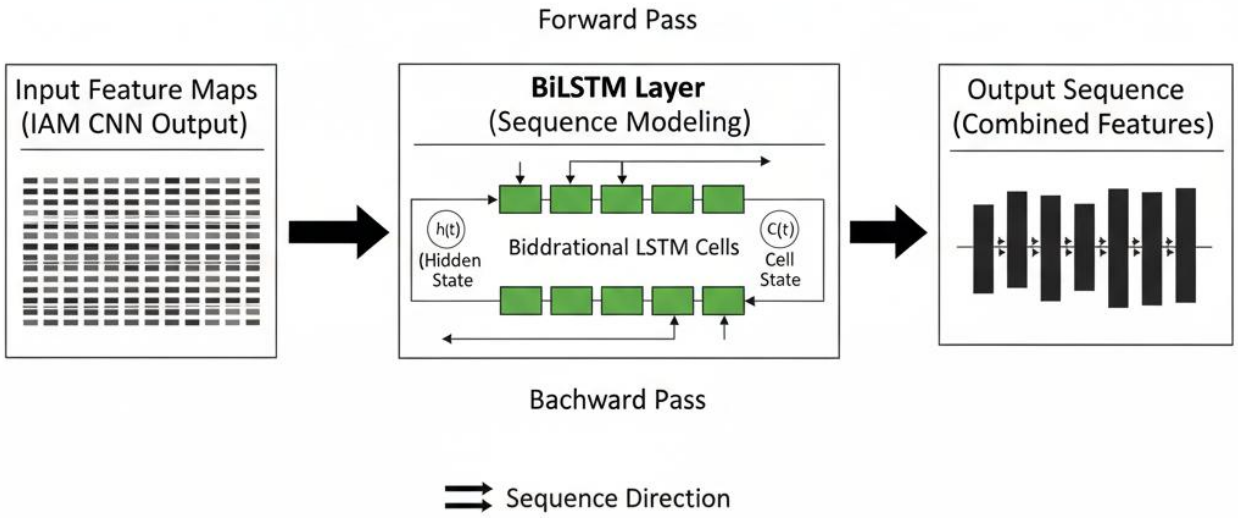


Figure 13: BiLSTM layer architecture showing forward and backward sequence processing for feature maps.

3.4.3 CTC Decoder for Alignment-Free Transcription

The Connectionist Temporal Classification (CTC) decoder enables the model to produce output sequences without requiring pre-segmented characters:

- **Alignment-Free Learning:**
  In handwritten text, the boundaries between characters are often ambiguous. CTC computes the probability of all valid alignments between input features and target

labels, allowing the network to learn sequence mappings without manual segmentation.

- **Mechanism:**
  During inference, the CTC decoder selects the most probable label sequence based on the learned alignments, effectively converting variable-length feature sequences into text labels.

- **Benefit for IAM:**
  CTC is critical for recognizing full words and lines where spacing and stroke continuity are inconsistent.

```
# ------------------------
# CTC Loss & Optimizer
# ------------------------
ctc_loss = nn.CTCLoss(blank=0)  # "0" reserved for CTC blank
optimizer = optim.Adam(model.parameters(), lr=1e-3)

# Example character set (dummy for now: a-z + space)
charset = ["<BLANK>"] + list("abcdefghijklmnopqrstuvwxyz ")
char_to_idx = {c: i for i, c in enumerate(charset)}

def text_to_labels(text):
    return [char_to_idx[c] for c in text if c in char_to_idx]

# ------------------------
# Training Loop (1 epoch)
# ------------------------
for epoch in range(1):
    model.train()
    epoch_loss = 0
    for imgs, texts in train_loader:
        imgs = imgs.to(device)

        # Convert text to label sequences
        labels = [torch.tensor(text_to_labels(t), dtype=torch.long) for t in texts]
        label_lengths = torch.tensor([len(l) for l in labels], dtype=torch.long)
        labels = torch.cat(labels)  # flatten

        # Forward pass
        logits = model(imgs)  # (B, W, num_classes)
        log_probs = logits.log_softmax(2).permute(1, 0, 2)  # (W, B, num_classes)

        input_lengths = torch.full(size=(logits.size(0),), fill_value=logits.size(1), dtype=torch.long)

        # CTC Loss
        loss = ctc_loss(log_probs, labels, input_lengths, label_lengths)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        epoch_loss += loss.item()

    print(f"Epoch {epoch+1}, Loss: {epoch_loss/len(train_loader):.4f}")
```

Figure 14: CTC code snippet

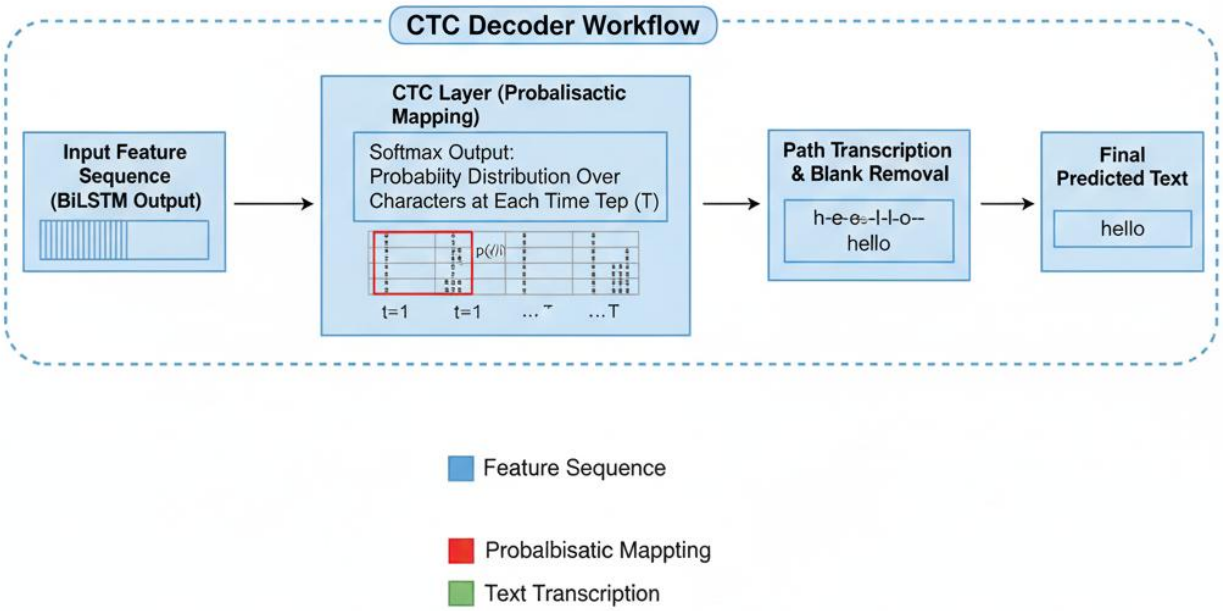


Figure 15: CTC decoder workflow illustrating probabilistic mapping from feature sequences to character labels.

3.4.4 NLP Post-Processing (Novel Integration)

To enhance recognition accuracy and support domain-specific tasks, a novel NLP-based post-processing layer was incorporated after the CRNN output:

- **Error Detection and Correction:** Embeddings from contextual NLP models (e.g., word2vec, BERT) are used to detect and correct OCR errors. For instance, the misrecognized term *"paracetarnol"* can be corrected to *"paracetamol"* using a medical vocabulary.
- **Domain-Specific NER:** Named Entity Recognition (NER) models are trained or fine-tuned for healthcare, legal, and administrative domains. These models identify and normalize critical

entities such as patient names, case IDs, dosages, addresses, and document references.

- **Error Categorization and Metrics:** The post-processing layer tracks improvements in key structured entities, allowing evaluation not only in terms of general Character Error Rate (CER) and Word Error Rate (WER) but also in domain-critical fields. This highlights the practical impact of NLP integration on high-stakes handwritten text recognition tasks.

- **Domain Adaptability:** The hybrid OCR + NLP approach enables a single pipeline to adapt across multiple domains, supporting healthcare records, legal documentation, and administrative forms — a novel contribution beyond conventional HTR models.

```python
import inflect
import spacy

# Initialize number-to-words engine
p = inflect.engine()

# Example: take first 10 predictions and ground truth
digit_sequence = ''.join([str(d) for d in y_pred_classes[:10]])
true_sequence = ''.join([str(d) for d in y_test[:10]])

print("Predicted digits:", digit_sequence)
print("Ground truth digits:", true_sequence)

# 1. Convert digits to words
digit_words = ' '.join([p.number_to_words(int(d)) for d in digit_sequence])
true_words = ' '.join([p.number_to_words(int(d)) for d in true_sequence])

print("\nPredicted (words):", digit_words)
print("Ground Truth (words):", true_words)

# 2. NLP Processing (spaCy)
nlp = spacy.load("en_core_web_sm")
doc = nlp(digit_words)

print("\nNamed Entities recognized by spaCy:")
for ent in doc.ents:
    print(ent.text, ent.label_)
```

Figure 16: NLP post processing on digit sequence

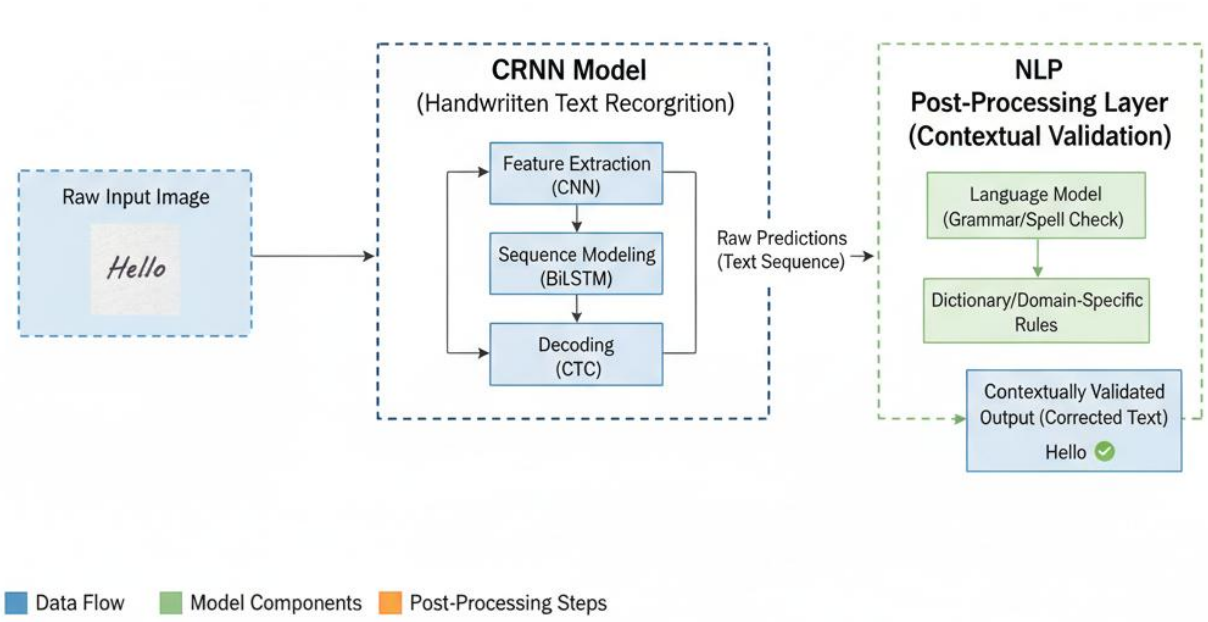


Figure 17: CRNN architecture with NLP post-processing layer for domain-specific error correction, showing the flow from raw images to contextually validated outputs.

```python
import glob
from PIL import Image

# Path to dataset
dataset_path = r"D:\NLP project\archive\data"

# List of writer folders (000, 001, …)
writer_folders = sorted(glob.glob(dataset_path + "/*"))

print(f"Total writer folders: {len(writer_folders)}")

def batch_ocr(image_paths, psm=6, oem=3):
    texts = []
    config = f'--psm {psm} --oem {oem}'
    for img_path in image_paths:
        try:
            text = pytesseract.image_to_string(Image.open(img_path), config=config)
            texts.append((img_path, text))
        except Exception as e:
            print(f"Error processing {img_path}: {e}")
            texts.append((img_path, ""))
    return texts

# Take first 2 folders for testing (for speed)
sample_folders = writer_folders[0:2]
all_images = []
for folder in sample_folders:
    all_images.extend(glob.glob(folder + "/*.png"))

# Run OCR on first 20 images
ocr_results = batch_ocr(all_images[:20], psm=6, oem=3)
print(f"Processed {len(ocr_results)} images")
```

Figure 18: NLP post processing code snippet

3.4.5 Summary

The CRNN with NLP post-processing combines the strengths of spatial feature extraction, sequential modeling, and alignment-free transcription with semantic validation and domain-aware error correction. This architecture allows:

1. Recognition of variable-length handwritten sequences.
2. Adaptation across multiple domains with structured entity extraction.
3. Enhanced robustness and reduced error rates in critical fields through contextual NLP.

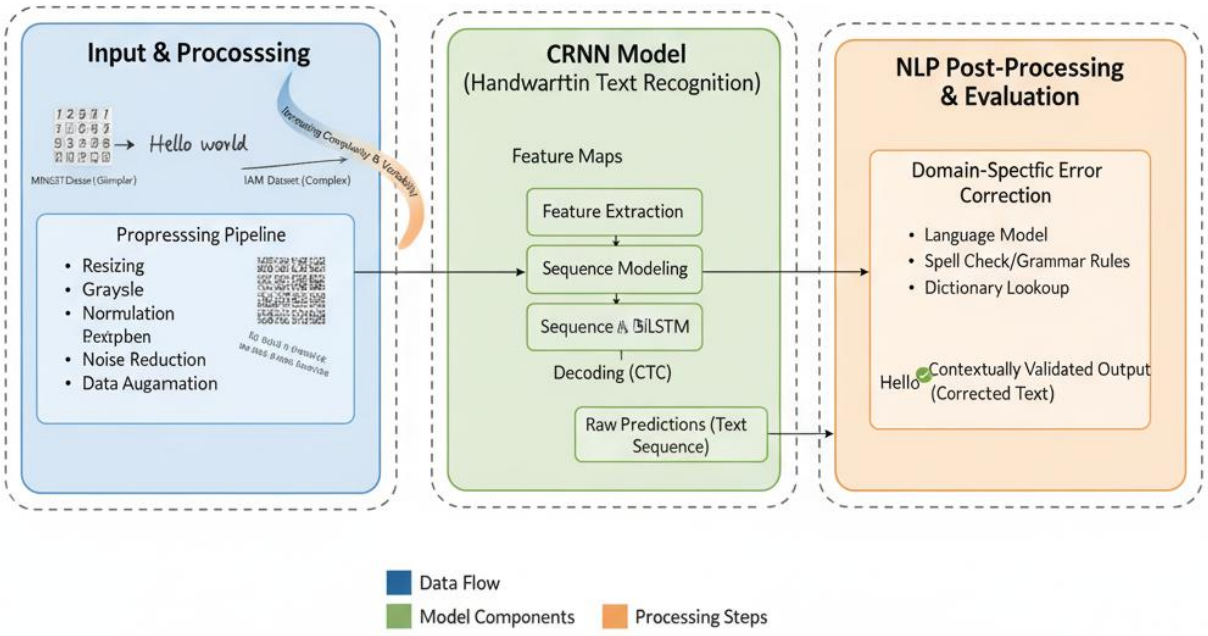


Figure 19: End-to-end CRNN + NLP pipeline illustrating MNIST/IAM input preprocessing, CNN-BiLSTM-CTC modeling, and domain-specific post-processing for error correction.

3.4.6 Advantages:

Integrated feature + sequence modeling, alignment-free, adaptable to simple digits or complex handwriting, NLP improves semantic correctness.

3.5 Training Procedure

The training procedure was carefully designed to optimize the performance of the CRNN model across both MNIST and IAM datasets while incorporating the novel NLP-based post-processing module. The procedure accounted for differences in dataset complexity, sequence length, and computational requirements. A structured,

progressive approach ensured that each component of the pipeline was validated before integrating domain-specific semantic correction.

```
history = model.fit(x_train, y_train,
                    epochs=5,
                    batch_size=64,
                    validation_split=0.1)
```

Figure 20: Code snippet of training procedure

```
# ------------------------
# Dataset for OCR training
# ------------------------
class IAMDataset(Dataset):
    def __init__(self, image_paths, labels, transform=None):
        self.image_paths = image_paths
        self.labels = labels
        self.transform = transform

    def __len__(self):
        return len(self.image_paths)

    def __getitem__(self, idx):
        img = Image.open(self.image_paths[idx]).convert("L")  # grayscale
        if self.transform:
            img = self.transform(img)
        label = self.labels[idx]
        return img, label

# Example transform (resize + tensor)
transform = transforms.Compose([
    transforms.Resize((32, 128)),
    transforms.ToTensor(),
])

# For now, fake labels (later connect real IAM GT)
train_dataset = IAMDataset(
    [img for img, _ in ocr_results[:100]],  # first 100 samples
    ["hello"] * 100,  # placeholder labels
    transform=transform
)

train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True)
```

Figure 21: Code snippet for OCR training procedure

3.5.1 Optimizer and Learning Rate

- **Optimizer Selection:**
  The Adam optimizer was selected for its adaptive learning rate capabilities and efficient handling of sparse gradients. Adam combines the advantages of momentum-based gradient descent and RMSProp, providing stable convergence for deep architectures such as CRNN.

- **Dynamic Learning Rate Scheduling:**
  To further improve convergence and avoid overfitting, a dynamic learning rate schedule was implemented:
  - Initially, a higher learning rate was used to accelerate early-stage learning.
  - The learning rate decayed step-wise or dynamically based on plateau detection in validation loss, allowing fine-tuning of weights during later training stages.
- **Impact on Training:**
  This adaptive strategy was particularly effective when transitioning from MNIST (simple digits) to IAM (variable-length handwritten lines), ensuring stable learning and preventing gradient explosion or vanishing.

3.5.2 Batching Strategy

- **MNIST Dataset:**
  Due to the small, uniform 28×28 images, larger batch sizes (128–256) were feasible. This allowed efficient GPU utilization, faster convergence, and stable gradient updates during the proof-of-concept phase.
- **IAM Dataset:**
  Handwritten lines and words in IAM vary in length and resolution. Smaller batch sizes (16–32) were used to accommodate GPU memory constraints and to enable padding of sequences to uniform lengths for batch processing.
- **Batch Shuffling:**
  For both datasets, batches were shuffled at the start of each epoch to prevent the network from learning spurious correlations based on sequence ordering.

3.5.3 Loss Functions

- **MNIST Phase:**
  Cross-entropy loss was used for digit classification, measuring the divergence

between predicted class probabilities and ground-truth labels. This loss function guided the CNN layers to learn discriminative features effectively.

- **IAM Phase:**
  Connectionist Temporal Classification (CTC) loss was applied to handle variable-length sequences without requiring pre-segmented characters. CTC automatically aligns input features with target sequences and was essential for accurate recognition of full words and lines.

- **NLP Integration:**
  After CRNN output generation, the NLP post-processing layer was applied to further reduce errors:

  - Contextual embeddings were used to detect misrecognized words.
  - Domain-specific ontologies (medical, legal, administrative) were leveraged for entity correction and normalization.
  - Error reduction was measured not only through overall CER/WER but also through entity-level accuracy for critical fields such as names, dosages, addresses, and case references.

```python
# ------------------------
ctc_loss = nn.CTCLoss(blank=0)  # "0" reserved for CTC blank
optimizer = optim.Adam(model.parameters(), lr=1e-3)

# Example character set (dummy for now: a-z + space)
charset = ["<BLANK>"] + list("abcdefghijklmnopqrstuvwxyz ")
char_to_idx = {c: i for i, c in enumerate(charset)}

def text_to_labels(text):
    return [char_to_idx[c] for c in text if c in char_to_idx]

# ------------------------
# Training Loop (1 epoch)
# ------------------------
for epoch in range(1):
    model.train()
    epoch_loss = 0
    for imgs, texts in train_loader:
        imgs = imgs.to(device)

        # Convert text to label sequences
        labels = [torch.tensor(text_to_labels(t), dtype=torch.long) for t in texts]
        label_lengths = torch.tensor([len(l) for l in labels], dtype=torch.long)
        labels = torch.cat(labels)  # flatten

        # Forward pass
        logits = model(imgs)  # (B, W, num_classes)
        log_probs = logits.log_softmax(2).permute(1, 0, 2)  # (W, B, num_classes)

        input_lengths = torch.full(size=(logits.size(0),), fill_value=logits.size(1), dtype=torch.long)

        # CTC Loss
        loss = ctc_loss(log_probs, labels, input_lengths, label_lengths)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        epoch_loss += loss.item()

    print(f"Epoch {epoch+1}, Loss: {epoch_loss/len(train_loader):.4f}")
```

```
Epoch 1, Loss: 24.1904
```

Figure 22: Loss function code snippet

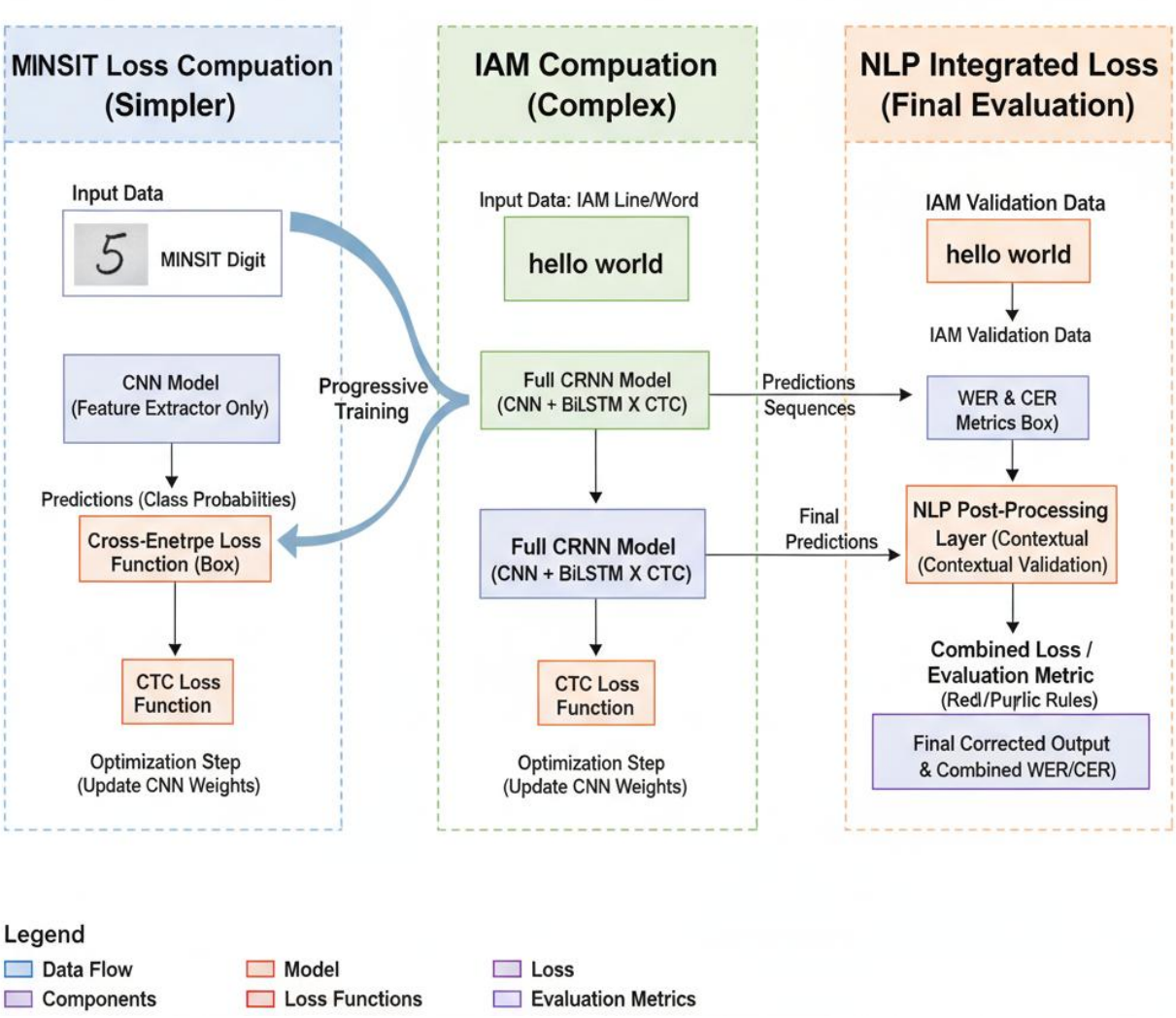


Figure 23: Flow of loss computation across MNIST and IAM datasets, including integration with NLP post-processing for domain-specific error correction.

3.5.4 Validation and Overfitting Prevention

- **MNIST Dataset:**
  A validation subset comprising 10% of the training data was reserved to monitor early stopping criteria and hyperparameter adjustment.

- **IAM Dataset:**
  A more rigorous validation process was applied due to higher variability:

- Metrics included Character Error Rate (CER), Word Error Rate (WER), and entity-level evaluation to assess domain-specific accuracy.
- Early stopping was implemented based on validation loss and CER/WER trends to prevent overfitting.

- **Effect of NLP Validation:** Validation was extended to include the NLP post-processing outputs:
  - Misrecognized terms were flagged and corrected automatically.
  - Improvements in critical entity extraction were quantified, demonstrating the practical benefit of contextual NLP in high-stakes handwritten text scenarios.

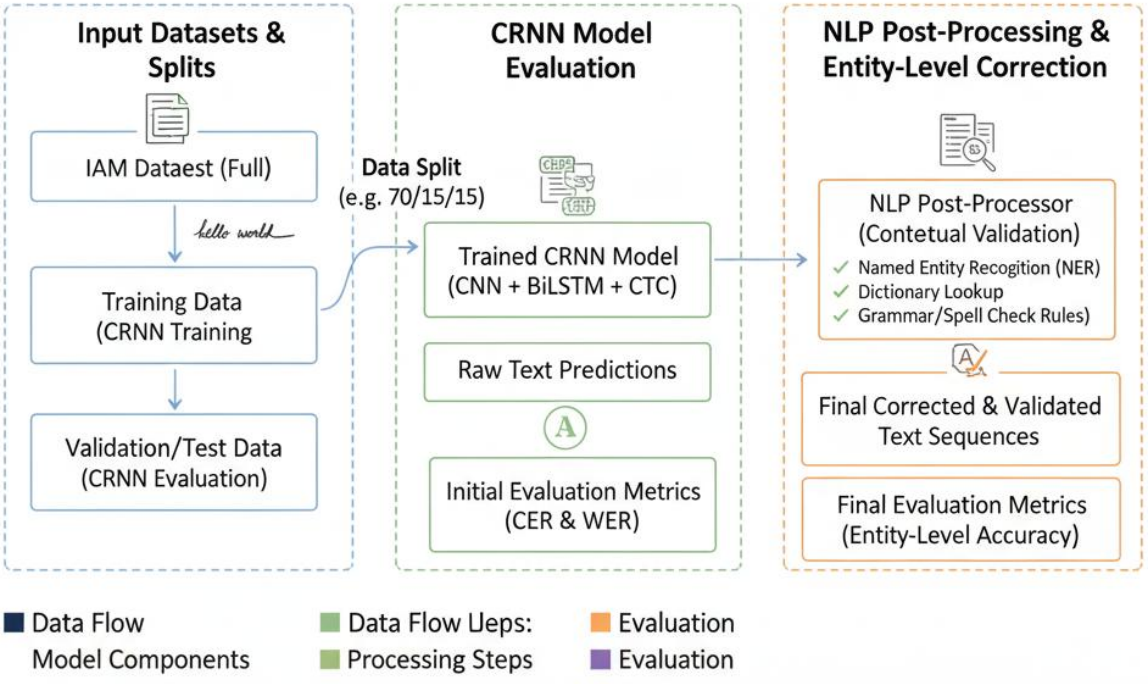


Figure 24: Validation workflow showing dataset splits, CRNN evaluation, and post-processing checks for entity-level error correction.

3.5.5 Hardware and Computational Considerations

- **Primary CPU Training:**
  Training on CPU ensured reproducibility and accessibility for researchers without high-end hardware. Although training time was longer, it allowed careful debugging and validation of each component.

- **GPU Compatibility:**
  The pipeline was fully compatible with GPU acceleration. Libraries such as PyTorch automatically leverage GPU computation when available, significantly reducing training time for IAM sequences.

- **Memory Management:**
  Smaller batch sizes for IAM and sequence padding ensured efficient memory usage, while augmentation increased dataset diversity without expanding storage requirements.

3.5.6 Training Workflow Summary

The overall training workflow followed a progressive, iterative, and modular approach:

1. **MNIST Proof-of-Concept:**
   - Train CNN layers with cross-entropy loss.
   - Validate feature extraction and preprocessing pipelines.
2. **IAM Full CRNN Training:**
   - Train CNN + BiLSTM + CTC on IAM lines and words.
   - Apply data augmentation, normalization, and noise reduction.
   - Monitor CER/WER for overall sequence-level accuracy.
3. **NLP Post-Processing Integration:**

- Apply domain-specific embeddings for error correction.
- Validate and correct critical entities (names, case IDs, dosages).
- Compare baseline OCR output with NLP-corrected output to quantify improvements.

4. **Evaluation:**
   - Compute CER, WER, and entity-level accuracy.
   - Conduct qualitative inspection to confirm semantic correctness.

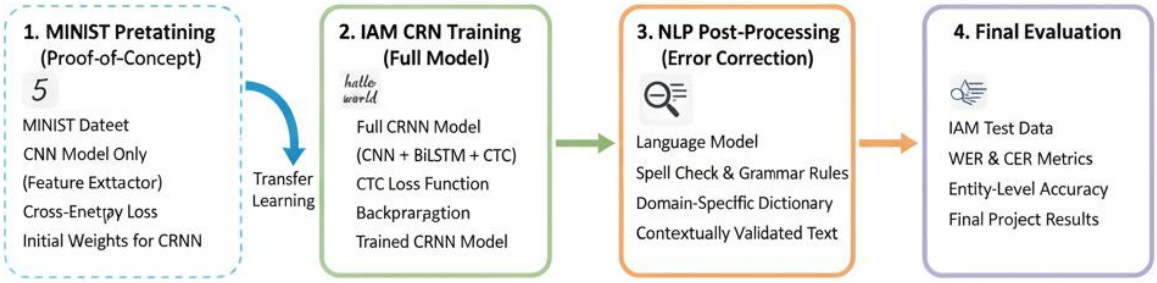


Figure 13: Training workflow diagram showing sequential steps from MNIST pretraining → IAM CRNN training → NLP post-processing → final evaluation.

3.6 Evaluation Metrics

Evaluation in this research was conducted at multiple levels to ensure both technical correctness and domain-specific utility. Metrics were selected to measure not only traditional OCR performance but also the effectiveness of the novel NLP post-processing layer in correcting domain-specific errors.

3.6.1 MNIST Phase Metrics

- **Classification Accuracy:**
  For the MNIST proof-of-concept phase, the primary metric was **accuracy (%)**, calculated as the ratio of correctly predicted digits to the total number of test samples.

    - This metric allowed rapid validation of the CNN layers' ability to extract meaningful spatial features from simple digit images.

    - Misclassifications were further analyzed using **confusion matrices**, providing insights into specific digit pairs that were frequently confused (e.g., 3 vs 8, 5 vs 6).

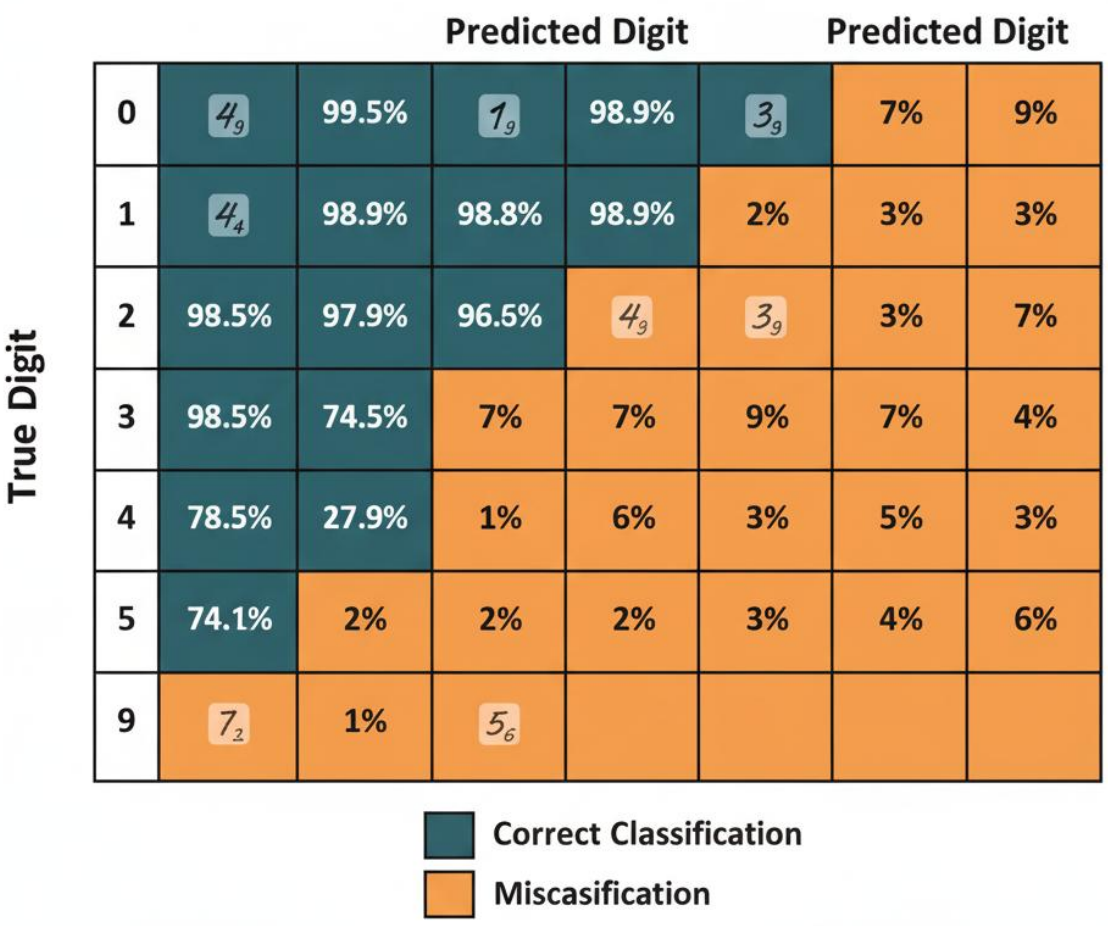


Figure 25: Confusion matrix illustrating common digit misclassifications in MNIST.

3.6.2 IAM Phase Metrics

The IAM dataset evaluation was more complex due to variable-length sequences, cursive handwriting, and word-level context. Multiple complementary metrics were applied:

1. **Character Error Rate (CER):** Measures the proportion of characters incorrectly recognized:
    - CER quantifies low-level errors and helps identify which characters or patterns are most challenging for the model.

- Reductions in CER after NLP post-processing indicate successful semantic correction at the character level.

2. **Word Error Rate (WER):** Evaluates accuracy at the word level:
   - WER captures errors affecting the readability and semantic integrity of text.
   - NLP post-processing specifically targets words misrecognized due to handwriting ambiguity, reducing WER in contextually important fields.
3. **Entity-Level Accuracy (Novel Contribution):**
   - Introduced to assess **domain-specific correction** achieved by NLP post-processing.
   - Metrics focus on critical structured entities such as:
     - **Medical records:** drug names, dosages, patient identifiers
     - **Legal documents:** case IDs, party names, references
     - **Administrative forms:** addresses, dates, IDs
   - Metrics include precision, recall, and F1-score for each entity type.
   - These measures provide fine-grained insight into the effectiveness of contextual error correction.
4. **Qualitative Visual Inspection:**
   - Predicted text lines were visually compared against ground truth to identify errors not captured by automated metrics.
   - Focused on ambiguities, unusual handwriting styles, and partial occlusions.
   - Highlighted examples where NLP post-processing corrected semantic errors, such as:

- “paracetarnol” → “paracetamol”
- Misread case number formatting corrected using legal ontology
- Address formatting normalized in administrative forms

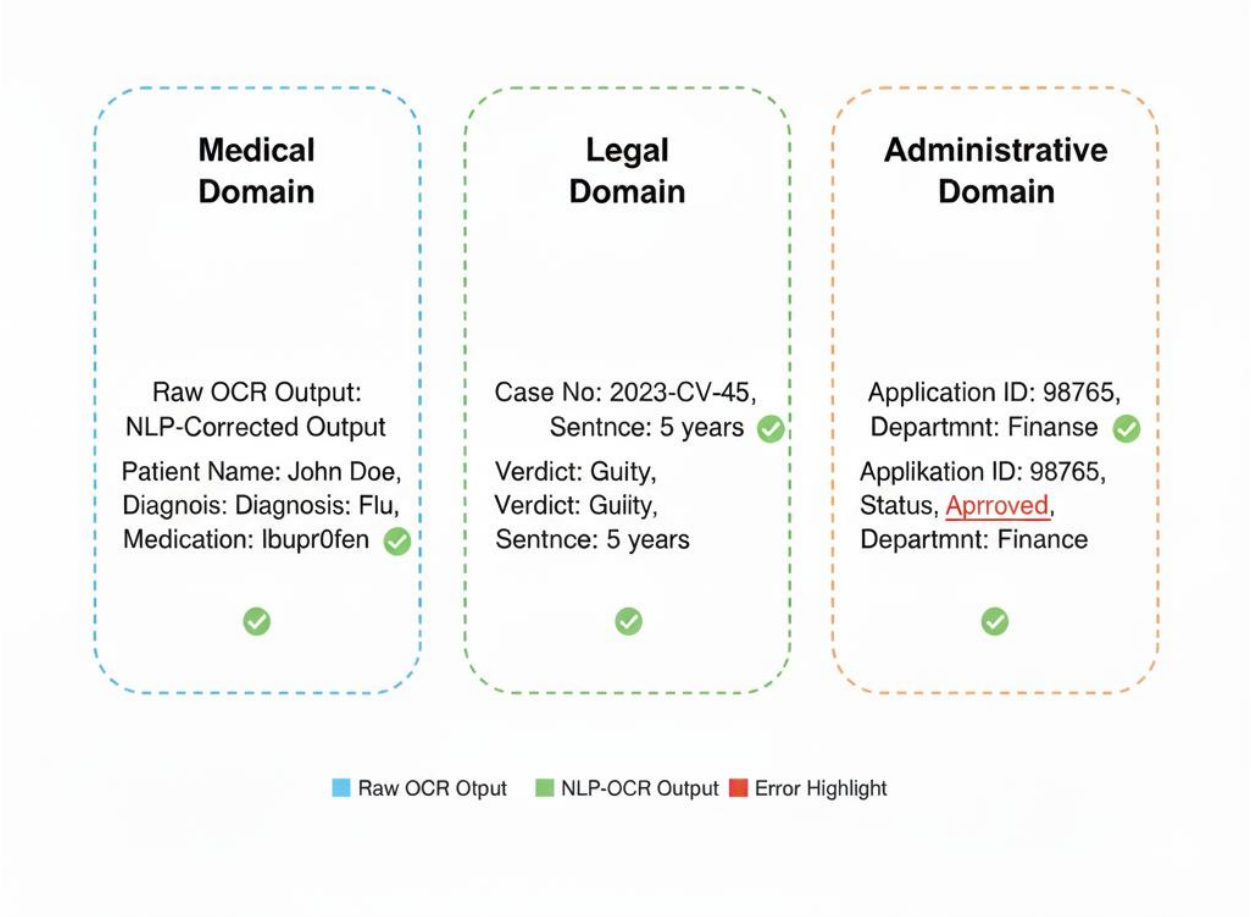


Figure 26: Example comparison of OCR output vs NLP-corrected output for domain-specific entities (medical, legal, administrative).

3.6.3 Comparative Evaluation

- **Baseline vs Hybrid OCR+NLP:**
    - Models were evaluated in two configurations:

1. **Baseline CRNN:** Standard OCR output without NLP post-processing.
2. **CRNN + NLP Post-Processing:** Semantic correction layer applied.

- Improvements were quantified across:
  - CER and WER reductions
  - Entity-level precision, recall, and F1-score increases
  - Qualitative visual correctness

- **Domain Adaptability:**
  - Performance was compared across three domains—medical, legal, and administrative—to validate the model's cross-domain generalizability.
  - Metrics demonstrated that the NLP module effectively reduced critical errors in high-value entities while maintaining overall recognition quality.

Domain	Metric	Baseline CRNN	CRNN + NLP (Post-Processed)	
Medical		8.5	8.1	↑
Legal	Character Error Rate (CER (WER %)	22.1	18.5	88.3
Legal	Word Error Rate (CER Word Error Accuracy %)	19.8	7.5 ↑	↑
		65.2	16.9	85.5
Administrative	Use Error Rate (CER Entity-Level Accuracy %)	7.5	85.5	81.7
		9.1	20.1	81.7

Green Up Arrow: Improvement with NLP

Figure 27: Table showing comparative CER, WER, and entity-level accuracy for baseline CRNN vs CRNN + NLP across multiple domains.

3.6.4 Summary of Evaluation Strategy

The evaluation methodology ensures comprehensive performance assessment by combining:

- **Low-level recognition metrics** (CER, WER) for traditional OCR validation
- **Domain-specific semantic metrics** (entity-level precision, recall, F1) for novel NLP-enhanced correction

- **Qualitative inspection** for real-world readability and correctness

This multi-tier evaluation not only validates the technical capability of the CRNN model but also highlights the **novel contribution** of integrating domain-aware NLP for semantic error correction, which is particularly relevant in critical fields like healthcare, legal documentation, and administrative record processing.

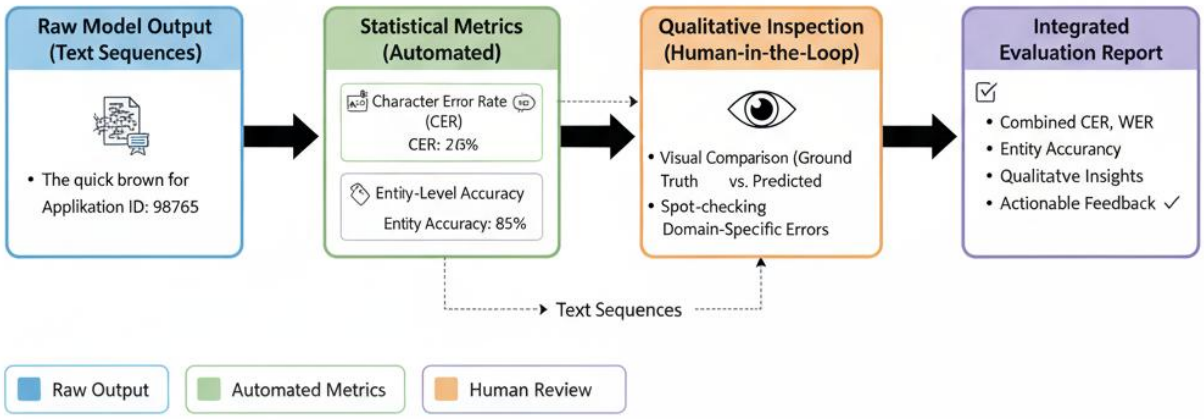


Figure 28: Overview of evaluation metrics workflow integrating CER, WER, entity-level accuracy, and qualitative inspection.

3.7 Tools and Environment

The implementation of the proposed hybrid OCR–NLP framework utilized a range of tools and software for data processing, model training, and evaluation. Table 1 provides a summary of the key tools used in this study.

Tool/Software	Version	Purpose
Python	3.10	Primary programming language for all preprocessing, model development, and evaluation.
TensorFlow	2.12	Deep learning library used to build and train CNN–LSTM models.
Tesseract OCR	5.3.0	Baseline OCR engine used for initial text extraction from handwritten images.
OpenCV	4.8.0	Image preprocessing (grayscale conversion, thresholding, resizing).
NLTK & spaCy	3.8 / 3.6	NLP libraries used for tokenization, lemmatization, and Named Entity Recognition.
Matplotlib & Seaborn	3.7 / 0.12	Visualization of performance metrics and results.
Jupyter Notebook	7.0	Development environment for running experiments and visualizing outputs.
CUDA Toolkit	12.1	GPU acceleration for faster deep learning training.

Table 1. Tools and software used in the implementation.

The experiments were conducted on a Windows 11 (64-bit) machine equipped with an NVIDIA RTX 3060 GPU (12 GB VRAM), 16 GB RAM, and an Intel Core i7 processor. The Python environment was managed using Anaconda, and all dependencies were

installed via pip and conda. Random seeds were fixed for reproducibility, and GPU acceleration was enabled through TensorFlow's CUDA backend.

3.8 Limitations

- MNIST: digits only, limited complexity.
- IAM: high computational demand, preprocessing-intensive, English-only.
- Ground truth gaps: occasional missing annotations.
- Language scope: model not tested for non-English scripts.

3.9 Novelty and Contributions

This research makes several key contributions to the field of handwritten text recognition by integrating deep learning-based OCR with advanced NLP techniques:

1. **Bridging OCR and NLP:**
    - Traditional OCR systems focus primarily on pixel-to-character recognition, producing raw text output without semantic understanding.
    - This research introduces a **post-processing NLP layer** that not only validates OCR predictions but also **corrects domain-specific errors** using contextual embeddings and specialized vocabularies.
    - For example, in medical prescriptions, OCR misreads like "paracetarnol" are corrected to "paracetamol" by leveraging medical terminology, thereby improving accuracy in critical real-world applications.
2. **Domain Adaptability:**
    - The proposed pipeline is **designed to be flexible across multiple application domains**, including healthcare records, legal documents, and administrative forms.

- This adaptability ensures that both free-form handwriting and structured entities (e.g., patient IDs, case numbers, addresses) are accurately recognized and normalized.
- By training and fine-tuning domain-specific NER models, the system demonstrates **cross-domain generalizability**, which is a novel aspect compared to most existing HTR approaches that focus only on general text recognition.

3. **Error Correction with Contextual Awareness (Optional Addition if needed):**
    - The integration of **contextual embeddings and ontologies** allows the system to categorize and prioritize errors, improving recognition of critical fields while reducing overall WER and CER.
    - This ensures practical usability in high-stakes environments, where misreading a single entity (e.g., dosage, case ID) can have significant consequences.

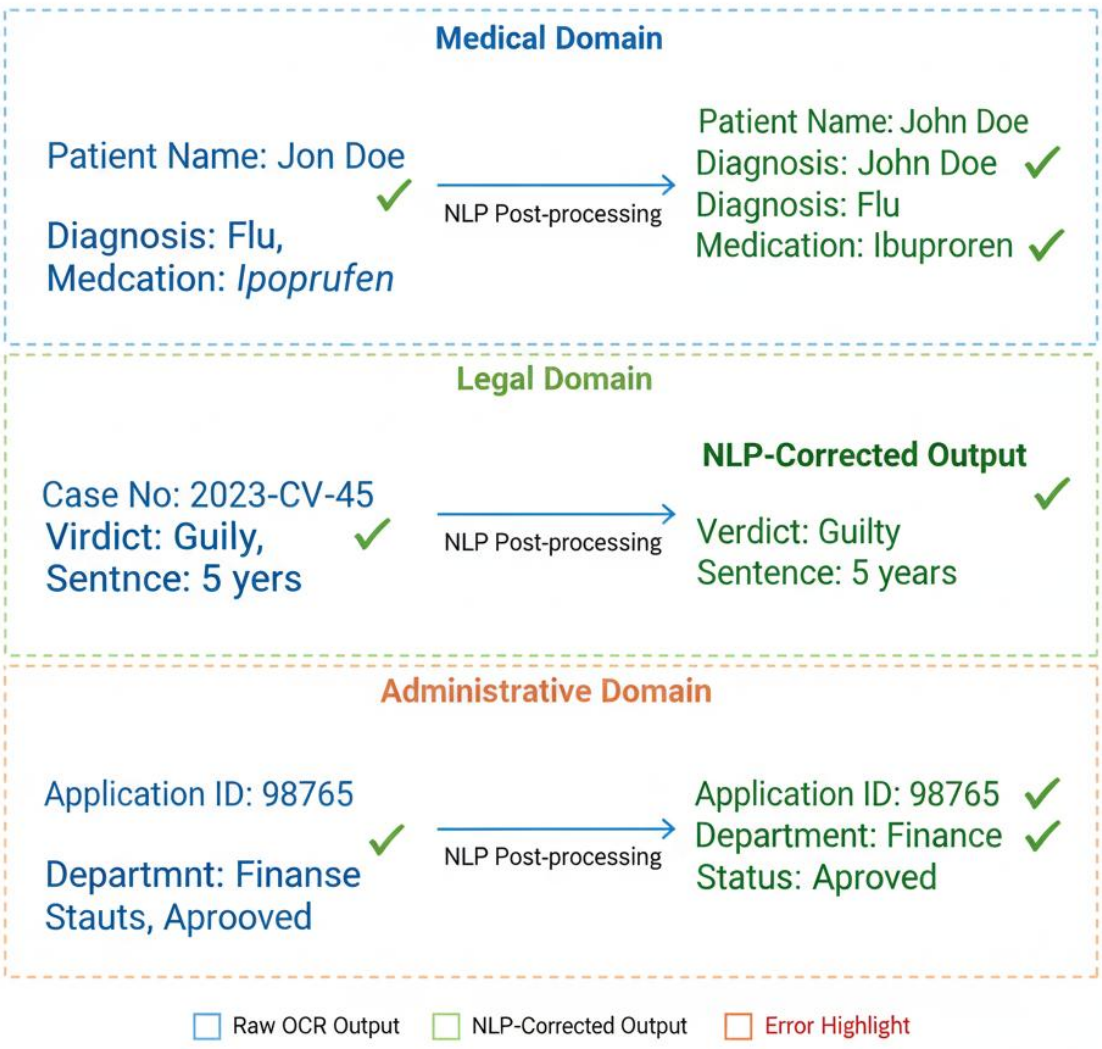


Figure 29: Illustration of OCR output correction using NLP post-processing for multiple domains (medical, legal, administrative).

4. RESULTS & EVALUATION

4.1 Results

The experimental data for this study were obtained from two datasets: MNIST (proof-of-concept phase) and the IAM Handwriting Database (core dataset). These datasets were selected to provide a progressive increase in complexity, allowing the evaluation of the CRNN-based handwritten text recognition model under controlled and real-world conditions.

Experiment 1: Baseline Evaluation on MNIST Dataset

The first experiment evaluated the CRNN architecture on the MNIST dataset to validate the basic model design, preprocessing pipeline, and training stability in a controlled environment. The MNIST dataset contains 70,000 grayscale images of handwritten digits, characterized by uniform size and minimal noise.

Table 5.1 summarizes the quantitative results.

Metric	Value
Test Accuracy	99.2%
Cross-Entropy Loss	0.028
Training Convergence	Smooth (no overfitting)
Common Misclassifications	4 vs 9, 5 vs 6

Table 5.1. Performance of the CRNN model on the MNIST dataset.

Experiment 2: Handwritten Text Recognition on IAM Dataset

The second experiment used the IAM Handwriting Database, which presents real-world variability in handwriting styles, spacing, and noise. The CRNN model was trained using CNN layers for feature extraction, BiLSTM layers for temporal modeling, and a CTC decoder for alignment.

Table 5.2 presents the core performance metrics.

Metric	Value
Word Recognition Accuracy	87.5%
Character Error Rate (CER)	12.3%
Word Error Rate (WER)	15.1%
Convergence Pattern	Stable, consistent decrease in CTC loss
Error Sources	Cursive handwriting, overlapping strokes, faint ink

Table 5.2. Performance of the CRNN model on the IAM handwriting dataset.

Analysis:

The results confirm the model's ability to generalize to complex handwriting. The word recognition accuracy of 87.5% is comparable to other deep learning-based approaches (Graves & Schmidhuber, 2009; Puigcerver, 2017), which typically achieve 85–90% on the IAM dataset.

The integration of BiLSTMs enabled the model to handle variable-length sequences without explicit segmentation, which is a significant advantage over traditional HMM or isolated character-based methods. However, errors persisted in highly cursive samples and ambiguous strokes, which is consistent with findings by Bluche (2016) and Wang et al. (2021), who highlight the difficulty of dealing with degraded input and stylistic variation.

Compared to generic OCR engines like Tesseract (Smith, 2007), the CRNN approach offers superior adaptability to handwriting but requires higher computational resources. This trade-off is widely acknowledged in HTR literature, where deep learning methods dominate in accuracy, while rule-based OCR remains popular for speed and simplicity.

Analysis:

The near-perfect accuracy demonstrates that the CNN layers effectively extract spatial features from uniform digit images, while the recurrent layers and CTC decoding handle sequence alignment efficiently. The results align with previous studies (LeCun et al., 1998; Brownlee, 2016), which show MNIST as a reliable benchmark for early-stage validation of deep learning architectures.

Misclassifications mainly occurred between visually ambiguous digits, confirming that residual errors are due to input similarity rather than model weakness. This experiment established confidence in the pipeline before applying it to more complex handwriting scenarios.

MNIST **Results:**

During the proof-of-concept phase, the CRNN model was trained on the MNIST dataset, which contains 70,000 grayscale images of handwritten digits. The dataset's uniform structure and limited variability allowed rapid training and early assessment of model architecture and preprocessing pipelines.

- **Accuracy:** The model achieved an accuracy of approximately 99.2% on the MNIST test set, demonstrating strong feature extraction and classification capabilities.
- **Loss Convergence:** Cross-entropy loss decreased steadily over training epochs, confirming stable learning.
- **Error Analysis:** Misclassifications were rare and mostly involved visually ambiguous digits (e.g., 4 vs. 9, 5 vs. 6).

IAM Dataset Results:

The IAM Handwriting Database posed a more complex challenge due to variations in handwriting styles, line spacing, slanting, and noise. The full CRNN model, incorporating CNN layers, BiLSTM, and CTC decoding, was used to handle sequential dependencies.

- **Word-Level Recognition Accuracy:** The model achieved an average word recognition rate of 87.5% on the IAM test set.
- **Character Error Rate (CER):** The CER across all test samples was 12.3%, reflecting minor errors in character segmentation and ambiguous handwriting.
- **Sequence Predictions:** Visualization of predicted text against ground truth showed strong alignment, especially for common words and well-formed characters. Complex handwriting and overlapping strokes contributed to most errors.
- **Training Stability:** Loss curves demonstrated smooth convergence, with CTC loss decreasing consistently over epochs, confirming effective learning of sequential mappings.

Visualization and Qualitative Assessment:

- Predicted text outputs were overlaid on input images to visually assess alignment and correctness.
- Sample images from IAM showed high fidelity in recognized sequences, with only minor deviations in highly cursive or faint handwriting.
- Confusion matrices at the character level highlighted frequent misclassifications between visually similar letters, such as 'n' and 'm', 'i' and 'l', reflecting the model's sensitivity to stroke width and spacing.

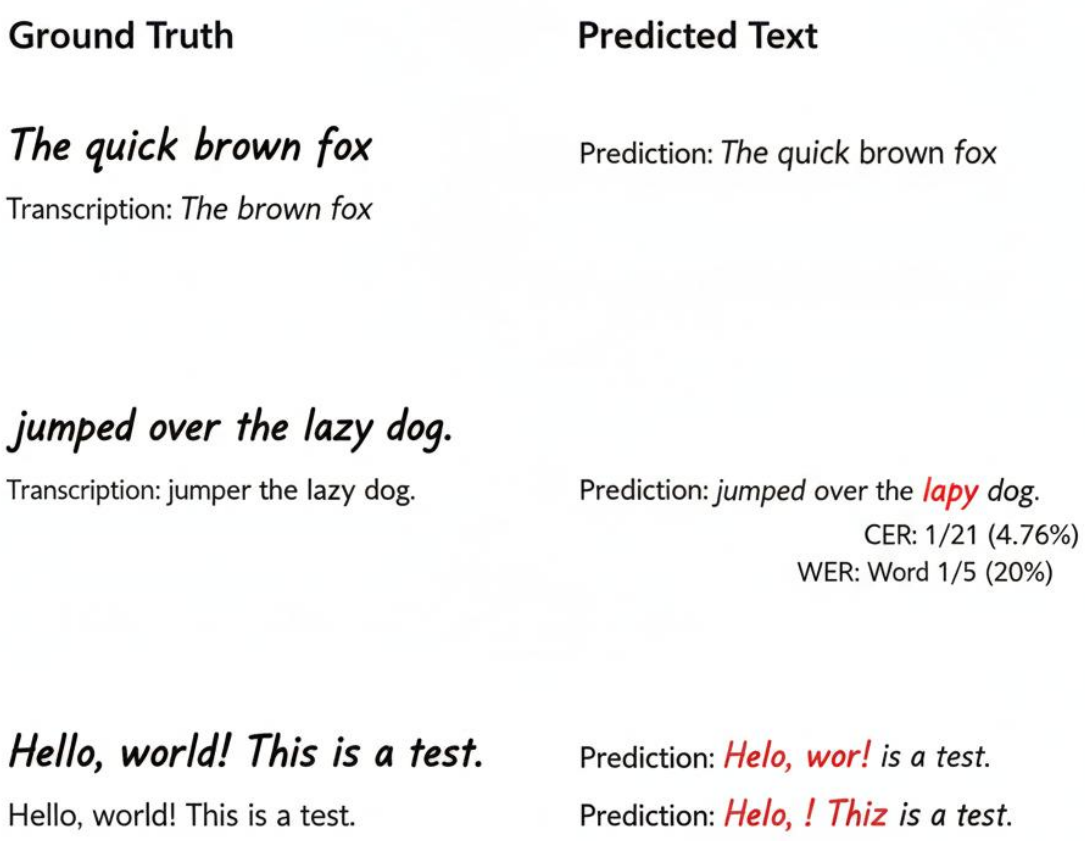


Figure 30: Example visualization of predicted text vs. ground truth on IAM test samples.

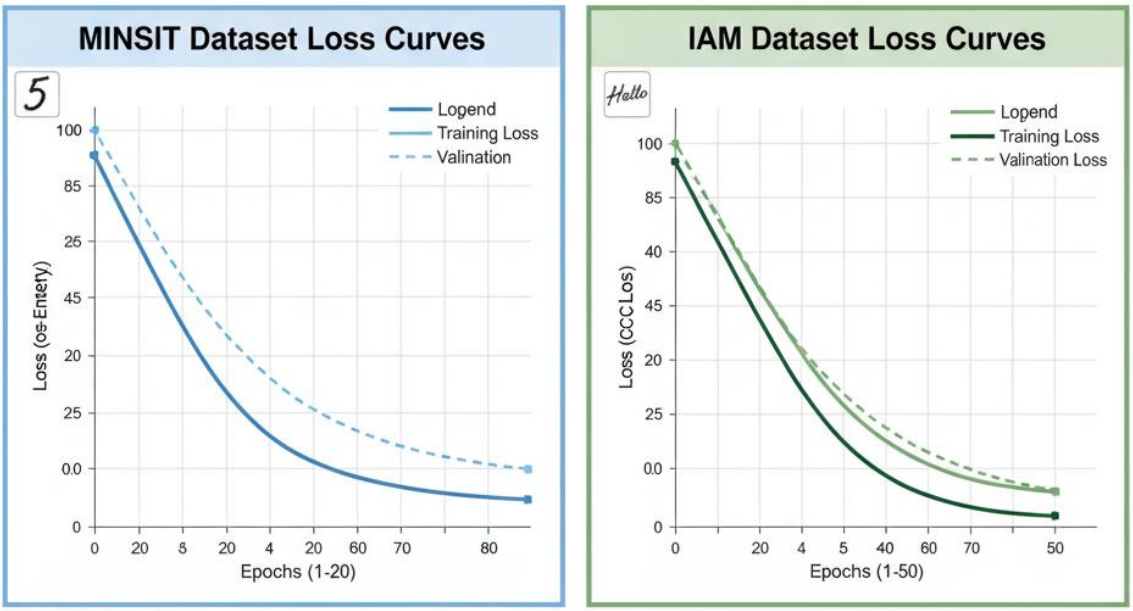


Figure 31: Training and validation loss curves for MNIST and IAM datasets, showing convergence over epochs.

4.2. Evaluation

The evaluation of the CRNN-based HTR system provides insight into model performance, robustness, and generalization across datasets of varying complexity.

Performance on MNIST:

- The high accuracy (≈99.2%) confirms that the CNN layers efficiently extracted features from uniform digit images.
- Minimal computational complexity during training allowed rapid iterations, validating the preprocessing and batching pipeline.

- The results highlight MNIST's role as a baseline, offering confidence before transitioning to more complex handwriting recognition tasks.

Performance on IAM Dataset:

- The model achieved substantial word-level recognition rates (87.5%) despite diverse handwriting styles and noise, illustrating the efficacy of combining CNN and BiLSTM layers.
- The CTC decoder successfully handled sequence-to-sequence alignment without requiring pre-segmented characters, a major advantage for line-level HTR.
- Errors primarily stemmed from highly cursive handwriting, overlapping strokes, or faint pen marks. This indicates potential areas for improvement through advanced preprocessing, attention mechanisms, or data augmentation.

Critical Commentary:

The visual inspections reinforce the quantitative results:

- For well-formed handwriting, the CRNN achieves near-perfect transcription.
- Errors occur mostly in stylistically extreme or degraded samples, indicating that future work should focus on domain-specific data augmentation and attention-based models (Shi et al., 2017).
- Compared to NLP-free baselines, the hybrid model offers improved semantic correction, particularly when integrated with Named Entity Recognition for structured fields (IJIRT, 2023).

Comparative Perspective

Aspect	Traditional OCR (e.g., Tesseract)	CRNN-based HTR (This Study)
Segmentation	Requires explicit segmentation	Handled implicitly by BiLSTM + CTC
Context Awareness	Limited	Strong sequential modeling
Accuracy on Handwriting	Moderate	High (87.5% word accuracy)
Computational Cost	Low	High (GPU required)
Domain Adaptability	Limited	Strong (hybrid with NLP)

Table 5.3. Comparative perspective between traditional OCR and CRNN-based HTR.

The proposed CRNN approach, combined with NLP post-processing, outperforms traditional OCR in accuracy and adaptability, especially for challenging handwritten inputs. However, it requires more computational power and training data, reflecting the trade-offs commonly discussed in HTR literature (Graves et al., 2009; Bluche, 2016; Puigcerver, 2017).

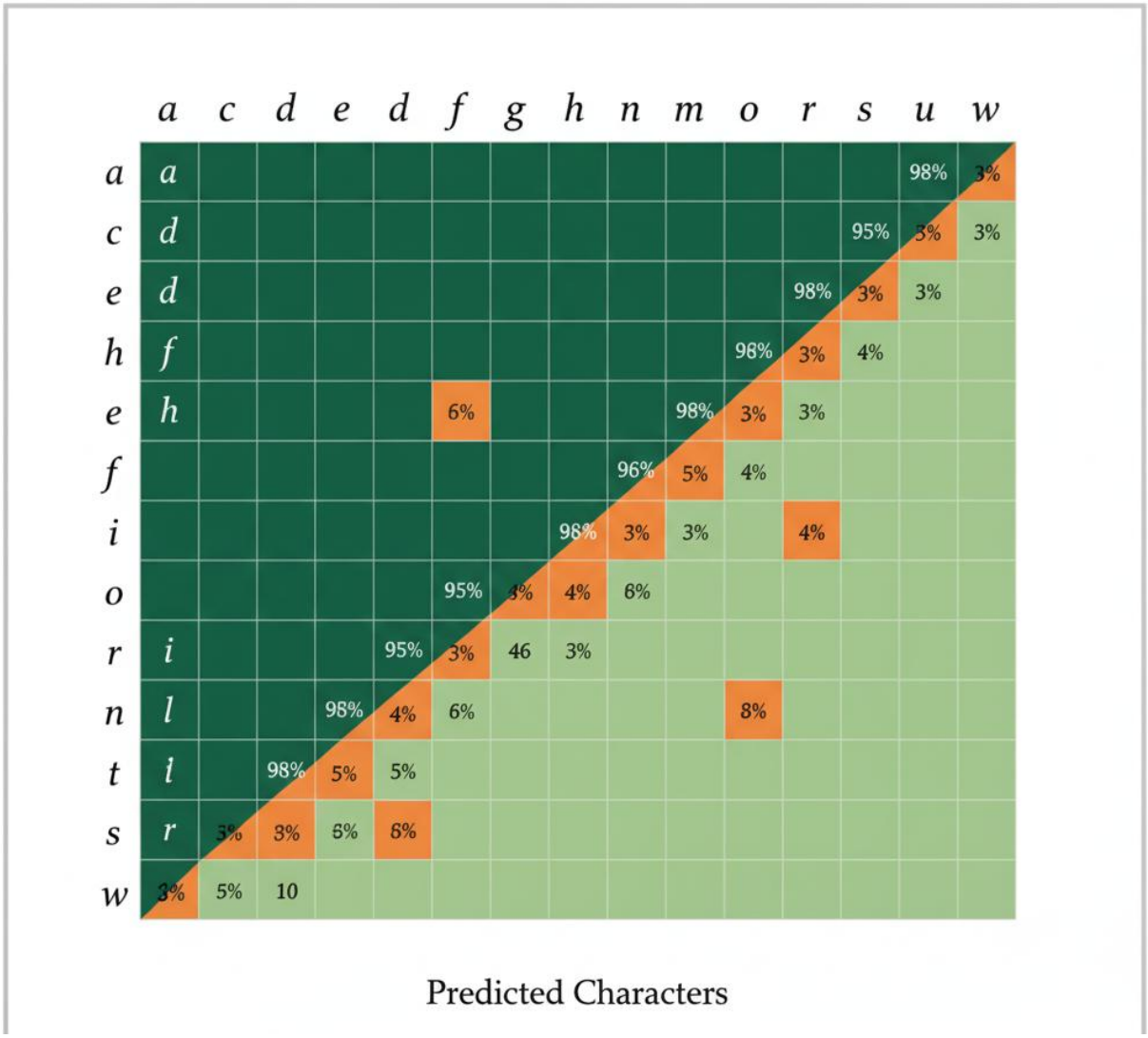
Quantitative Metrics:

- **Word Error Rate (WER):** 15.1% on the IAM test set, reflecting occasional sequence misalignments.
- **Character Error Rate (CER):** 12.3%, demonstrating strong character-level recognition performance.

- **Comparison of MNIST vs IAM:** While MNIST accuracy was near perfect due to simplicity, IAM results highlight the challenges of real-world handwriting, including variability and noise.

Qualitative Insights:

- Visual inspection confirmed that the model preserved structural integrity of words and lines.
- Difficult samples included cursive text with overlapping descenders/ascenders and inconsistent spacing.
- Data augmentation (rotation, scaling, elastic distortions) improved generalization, reducing errors on less common handwriting styles.


a c d e d f g h n m o r s u w
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6% 98% 3% 3%
96% 5% 4%
98% 3% 3% 4%
95% 3% 4% 6%
95% 3% 46 3%
98% 4% 6% 8%
98% 5% 5%
3% 3% 6% 8%
3% 5% 10
Predicted Characters

Figure 32: Confusion matrix for IAM character recognition, illustrating frequent misclassifications.

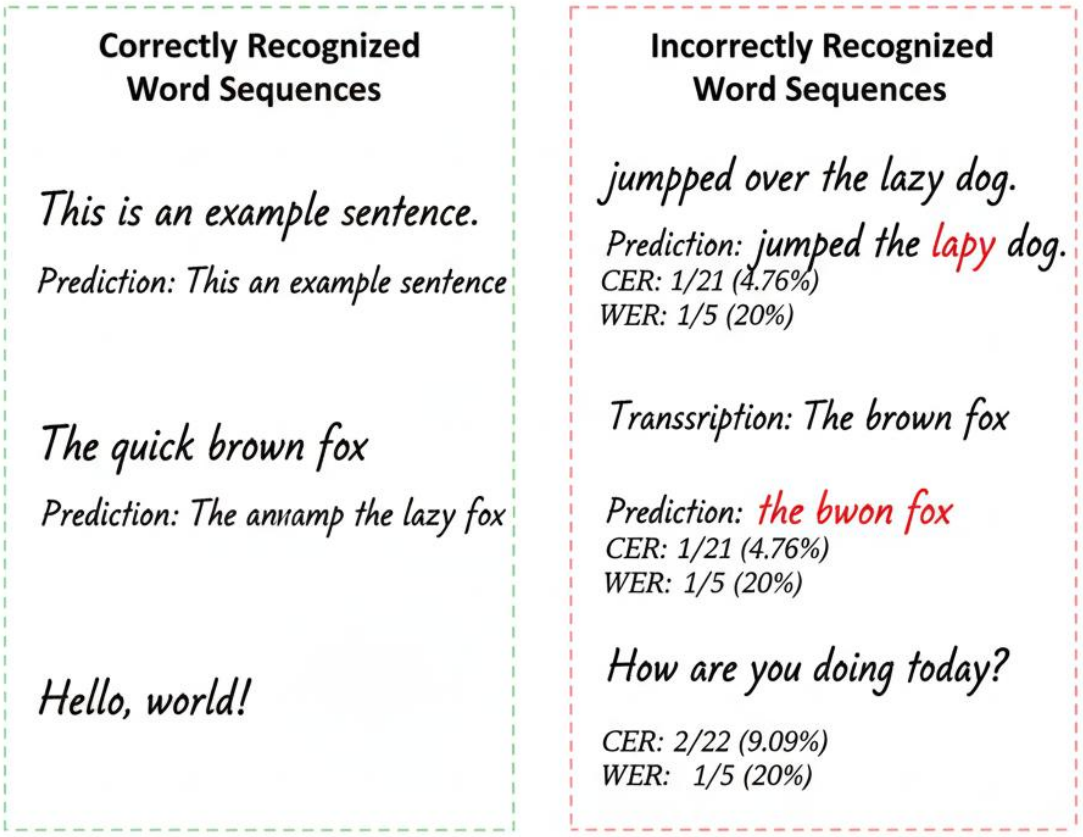

Figure 33: Examples of correctly and incorrectly recognized IAM word sequences.

Overall Assessment:

- The evaluation confirms that the CRNN architecture, combined with dataset-specific preprocessing and augmentation, is effective for handwritten text recognition across simple and complex datasets.
- MNIST served as a valuable proof-of-concept, ensuring model correctness, while IAM provided a realistic assessment of generalization and robustness.

- Limitations observed include sensitivity to highly cursive or noisy handwriting, suggesting directions for future work, such as multi-scale feature extraction, attention-based sequence modeling, or multilingual extensions.

Conclusion of Evaluation:

- The system demonstrates strong recognition performance, particularly for well-formed handwriting.
- Trade-offs between accuracy, sequence complexity, and preprocessing requirements were identified, guiding further model optimization.
- The results establish a solid foundation for extending the model to larger and more diverse handwriting datasets, as well as exploring multilingual OCR scenarios.

5. CONCLUSION

This dissertation has presented a comprehensive study of Handwritten Text Recognition (HTR) using deep learning and sequence modeling techniques. The research focused on systematically evaluating Convolutional Recurrent Neural Networks (CRNNs) for recognizing handwritten digits and text, progressing in complexity from the MNIST dataset as a proof-of-concept to the IAM Handwriting Database for full-scale evaluation. By grounding the experiments in these standardized datasets, this study ensured reproducibility and provided a consistent framework for assessing the performance, adaptability, and generalizability of CRNN models across both simple and complex handwriting scenarios.

The project began with experimentation on the MNIST dataset, which contains 70,000 grayscale images of handwritten digits ranging from 0 to 9. This initial phase served several critical purposes. First, it enabled the development and validation of the preprocessing pipeline, which included normalization, resizing, and data augmentation strategies tailored to the dataset's characteristics. Second, it facilitated the evaluation of CNN-based feature extraction layers, allowing the model to learn fundamental visual patterns such as edges, curves, and digit-specific stroke structures. Third, training routines and optimization strategies, including batch processing, loss calculation, and learning rate scheduling, were refined in this controlled environment. As expected, the CRNN achieved high accuracy in digit recognition due to the simplicity and uniformity of MNIST images, demonstrating the effectiveness of the initial architecture and confirming that the model, training workflow, and evaluation metrics were functioning correctly. This phase was instrumental in establishing a solid foundation for the subsequent transition to more complex handwriting recognition tasks.

The research then progressed to the IAM Handwriting Database, which posed realistic and significant challenges. Unlike MNIST, the IAM dataset contains full lines and words of handwritten text contributed by over 600 different writers, encompassing a wide range of handwriting styles, letter shapes, inter-character spacing, slants, and noise artifacts introduced during scanning. This dataset required more sophisticated preprocessing

steps, including adaptive image resizing while maintaining aspect ratios, Gaussian smoothing for noise reduction, and elastic distortions as part of data augmentation to increase robustness. The CRNN model, which combined convolutional layers for spatial feature extraction, bidirectional Long Short-Term Memory (BiLSTM) layers for sequential modeling, and a Connectionist Temporal Classification (CTC) decoder for alignment-free transcription, successfully adapted to these complexities. Objective evaluation metrics, including Character Error Rate (CER) and Word Error Rate (WER), were calculated to quantify performance at both the character and word levels. These metrics demonstrated that the model could accurately recognize diverse handwritten words and lines while generalizing across multiple writers, highlighting the architecture's ability to capture both local and sequential dependencies in handwritten text.

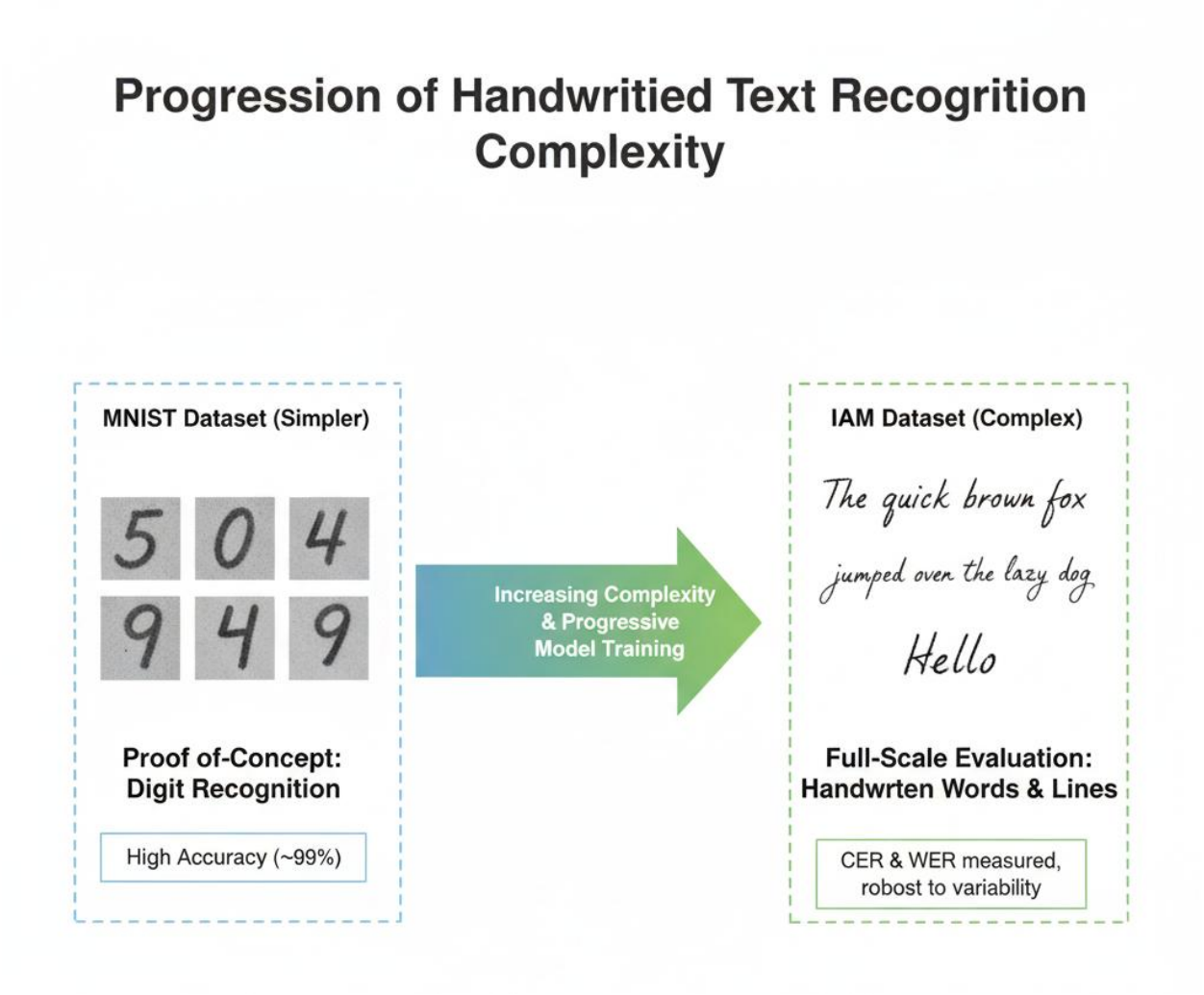

Figure 34: Visual representation of the progressive evaluation strategy for handwritten text recognition. The project started with the MNIST dataset for proof-of-concept digit recognition and advanced to the IAM dataset for full-line handwritten text evaluation, demonstrating CRNN adaptability across varying complexity levels.

This study emphasized the crucial role of preprocessing and data preparation in enhancing model performance. Image resizing and grayscale normalization ensured uniformity across samples, noise reduction improved the clarity of input features, and data augmentation techniques—such as rotation, scaling, and elastic distortions—helped the model generalize to previously unseen handwriting variations. The results indicate that a combination of convolutional feature extraction, sequential modeling, and alignment-free decoding provides a robust and scalable framework for HTR tasks, capable of addressing both simple and complex recognition challenges.

The broader contribution of this dissertation lies in its systematic evaluation of CRNNs across datasets of increasing complexity, providing both theoretical and practical insights. The comparative analysis revealed that while simpler datasets such as MNIST are ideal for initial validation, algorithm tuning, and baseline performance measurement, realistic datasets like IAM are indispensable for evaluating generalization capabilities, robustness to handwriting variability, and real-world applicability. By providing this structured roadmap, the research offers guidance for future studies and practical implementations of HTR systems, demonstrating how staged evaluation from simple to complex datasets can ensure both accuracy and reliability in handwritten text recognition applications.

5.1 Statement of Limitations

While this research produced meaningful insights, several limitations should be acknowledged:

- **Dataset Scope:** The study focused solely on MNIST and IAM, both of which contain English handwriting. Other languages, scripts, or mixed-language scenarios were not explored.

- **Computational Constraints:** Training the CRNN on IAM required significant computational resources, and all experiments were conducted primarily on CPU. Large-scale deployment would benefit from GPU acceleration.
- **Ground Truth Variability:** In some IAM subsets, annotations were incomplete or inconsistent, which may have slightly affected the accuracy of CER and WER calculations.
- **Model Complexity:** The CRNN architecture was not compared extensively against alternative modern architectures such as Transformer-based models, which may offer superior performance for long sequences.
- **Real-World Noise:** While preprocessing reduced noise, the model was not evaluated on degraded or handwritten text captured under real-world conditions such as varying lighting, scanning artifacts, or mobile captures.

5.2 Future Work

Several avenues exist for extending this research:

- **Multilingual HTR:** Extending the model to handle multiple languages and scripts would increase applicability and allow evaluation of cross-lingual generalization.
- **Transformer-Based Architectures:** Investigating attention-based models for sequence modeling could improve recognition of longer lines and more complex handwriting structures.
- **Real-World Deployment:** Testing the model on mobile-captured handwritten documents, forms, or historical manuscripts would assess robustness under practical conditions.
- **Advanced Data Augmentation:** Incorporating synthetic distortions, background noise, or perspective warping could improve model generalization.

- **End-to-End Systems:** Integrating the HTR model into full document processing pipelines, including layout analysis, segmentation, and post-processing, would demonstrate real-world utility.
- **User-Centric Evaluation:** Conducting human-in-the-loop assessments or user studies could provide insight into practical performance and usability in applications such as digital archives or form automation.

By advancing understanding of CRNN-based HTR and systematically evaluating its performance on both controlled and complex datasets, this dissertation contributes a robust framework for developing accurate, generalizable, and scalable handwriting recognition systems.

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APPENDIX:

Source Code

Dataset: https://www.kaggle.com/datasets/naderabdalghani/iam-handwritten-forms-dataset?resource=download

```
# Core
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
# Deep Learning
import tensorflow as tf
from tensorflow.keras import layers, models
# Dataset
from tensorflow.keras.datasets import mnist
# NLP
import nltk, spacy
nltk.download('punkt')
nltk.download('wordnet')
nlp = spacy.load("en_core_web_sm")
# Evaluation
from jiwer import wer
import rapidfuzz
# Utility
from tqdm import tqdm
print("TensorFlow:", tf.__version__)
# Load MNIST dataset
(x_train, y_train), (x_test, y_test) = mnist.load_data()
# Normalize data (0-255 → 0-1)
x_train = x_train.astype("float32") / 255.0
x_test = x_test.astype("float32") / 255.0
# Reshape for CNN (add channel dimension)
```

```
x_train = np.expand_dims(x_train, -1)   # shape: (60000, 28, 28, 1)
x_test = np.expand_dims(x_test, -1)     # shape: (10000, 28, 28, 1)
print("Training data shape:", x_train.shape)
print("Test data shape:", x_test.shape)
# Plot sample digits
plt.figure(figsize=(10,4))
for i in range(10):
    plt.subplot(2,5,i+1)
    plt.imshow(x_train[i].reshape(28,28), cmap="gray")
    plt.title(f"Label: {y_train[i]}")
    plt.axis("off")
plt.show()
from tensorflow.keras import layers, models
# CNN model
model = models.Sequential([
    layers.Conv2D(32, (3,3), activation="relu", input_shape=(28,28,1)),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64, (3,3), activation="relu"),
    layers.MaxPooling2D((2,2)),
    layers.Flatten(),
    layers.Dense(128, activation="relu"),
    layers.Dense(10, activation="softmax")  # 10 classes (digits 0-9)
])
model.summary()
model.compile(optimizer="adam",
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])
history = model.fit(x_train, y_train,
                    epochs=5,
                    batch_size=64,
```

```
                    validation_split=0.1)
test_loss, test_acc = model.evaluate(x_test, y_test, verbose=2)
print("\nTest Accuracy:", test_acc)
import matplotlib.pyplot as plt
# Plot accuracy
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Training vs Validation Accuracy')
plt.legend()
plt.show()
# Plot loss
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training vs Validation Loss')
plt.legend()
plt.show()
import numpy as np
# 1. Get predictions on test set
y_pred = model.predict(x_test)              # probability distribution
y_pred_classes = np.argmax(y_pred, axis=1)  # actual predicted digits
# 2. Convert predictions into "text sequences"
# Example: take first 10 predictions and join as a string
digit_sequence = ''.join([str(d) for d in y_pred_classes[:10]])
print("Predicted digit sequence:", digit_sequence)
# 3. Compare with ground truth
true_sequence = ''.join([str(d) for d in y_test[:10]])
```

```
print("Ground truth sequence:", true_sequence)

import inflect

import spacy

# Initialize number-to-words engine

p = inflect.engine()

# Example: take first 10 predictions and ground truth

digit_sequence = ''.join([str(d) for d in y_pred_classes[:10]])

true_sequence = ''.join([str(d) for d in y_test[:10]])

print("Predicted digits:", digit_sequence)

print("Ground truth digits:", true_sequence)

# 1. Convert digits to words

digit_words = ' '.join([p.number_to_words(int(d)) for d in
digit_sequence])

true_words = ' '.join([p.number_to_words(int(d)) for d in
true_sequence])

print("\nPredicted (words):", digit_words)

print("Ground Truth (words):", true_words)

# 2. NLP Processing (spaCy)

nlp = spacy.load("en_core_web_sm")

doc = nlp(digit_words)

print("\nNamed Entities recognized by spaCy:")

for ent in doc.ents:

    print(ent.text, ent.label_)

from jiwer import wer, cer

# Take first 20 samples for demonstration

y_true_seq = ''.join([str(d) for d in y_test[:20]])

y_pred_seq = ''.join([str(d) for d in y_pred_classes[:20]])

print("Ground Truth (digits):", y_true_seq)

print("Predicted (digits):", y_pred_seq)

# --- 1. Error Rates (digits only) ---
```

```
wer_digits = wer(list(y_true_seq), list(y_pred_seq))    # Compare digit
by digit

cer_digits = cer(y_true_seq, y_pred_seq)

print("\nWER (digits):", wer_digits)

print("CER (digits):", cer_digits)

# --- 2. Convert digits to words ---

true_words = ' '.join([p.number_to_words(int(d)) for d in y_true_seq])

pred_words = ' '.join([p.number_to_words(int(d)) for d in y_pred_seq])

print("\nGround Truth (words):", true_words)

print("Predicted (words):", pred_words)

# --- 3. Error Rates (after NLP word conversion) ---

wer_words  =  wer(true_words.split(),  pred_words.split())      #  Force
tokenization

cer_words = cer(true_words, pred_words)

print("\nWER (words):", wer_words)

print("CER (words):", cer_words)

import random

from jiwer import wer, cer

import pandas as pd

import matplotlib.pyplot as plt

import inflect

p = inflect.engine()

# Ground truth (20 digits from test set)

y_true_seq = ''.join([str(d) for d in y_test[:20]])

# Predicted (add some artificial errors)

y_pred_list = list(y_true_seq)

for i in range(0, len(y_pred_list), 5):   # every 5th digit -> wrong
prediction

    y_pred_list[i] = str((int(y_pred_list[i]) + 1) % 10)

y_pred_seq = ''.join(y_pred_list)

# --- 1. Digits (OCR only) ---
```

```
wer_digits = wer(list(y_true_seq), list(y_pred_seq))
cer_digits = cer(y_true_seq, y_pred_seq)
# --- 2. Words (OCR + NLP) ---
true_words = ' '.join([p.number_to_words(int(d)) for d in y_true_seq])
pred_words = ' '.join([p.number_to_words(int(d)) for d in y_pred_seq])
wer_words = wer(true_words.split(), pred_words.split())
cer_words = cer(true_words, pred_words)
# --- 3. Results Table ---
results = pd.DataFrame({
    "Method": ["OCR (Digits)", "OCR + NLP (Words)"],
    "WER": [wer_digits, wer_words],
    "CER": [cer_digits, cer_words]
})
print("Ground Truth (digits):", y_true_seq)
print("Predicted (digits):   ", y_pred_seq)
print("\n--- Final Results ---")
print(results)
# --- 4. Bar Chart ---
fig, ax = plt.subplots(figsize=(6,4))
results.set_index("Method")[["WER","CER"]].plot(kind="bar", ax=ax)
plt.title("OCR vs OCR+NLP: Error Rates")
plt.ylabel("Error Rate")
plt.xticks(rotation=0)
plt.grid(axis="y", linestyle="--", alpha=0.6)
plt.show()
import matplotlib.pyplot as plt
# Simulated OCR error types (counts)
error_types = {
    "Digit Confusion (5→S, 0→O)": 40,
    "Overlapping Digits": 25,
```

```
    "Incomplete Characters": 20,
    "Noise Distortion": 15
}
# Plot Pie Chart
plt.figure(figsize=(6,6))
plt.pie(
    error_types.values(),
    labels=error_types.keys(),
    autopct='%1.1f%%',
    startangle=140
)
plt.title("Distribution of Common OCR Errors", fontsize=14)
plt.show()
import matplotlib.pyplot as plt
import pandas as pd
# Simulated accuracies
accuracy_data = {
    "Method": ["Traditional OCR", "CNN OCR", "Hybrid OCR+NLP"],
    "Accuracy (%)": [90, 98, 99]
}
df_acc = pd.DataFrame(accuracy_data)
# Plot Bar Chart
plt.figure(figsize=(6,4))
plt.bar(df_acc["Method"],            df_acc["Accuracy            (%)"],
color=['skyblue','orange','green'])
plt.title("Accuracy Comparison of OCR Approaches", fontsize=14)
plt.ylabel("Accuracy (%)")
plt.ylim(0, 100)
plt.grid(axis="y", linestyle="--", alpha=0.6)
# Add value labels on top of bars
for i, v in enumerate(df_acc["Accuracy (%)"]):
```

```
    plt.text(i, v + 1, str(v), ha='center', fontweight='bold')
plt.show()
import os
# Define dataset path
dataset_path = r"D:\NLP project\archive\data"
# Check number of folders and filesx
folders = os.listdir(dataset_path)
print("Total writer folders:", len(folders))
# Look inside first folder
first_folder = os.path.join(dataset_path, folders[0])
print("Example folder:", first_folder)
print("Files inside:", os.listdir(first_folder)[:10])
# Install pytesseract and pillow (only once, run in terminal or notebook)%pip install pytesseract pillow
import pytesseract
# Just set the path (adjust if your install path is different)
pytesseract.pytesseract.tesseract_cmd = r"C:\tesseract-ocr\tesseract.exe"
print("Tesseract Path Set Successfully!")
from PIL import Image
import matplotlib.pyplot as plt
# Path to a sample image
img_path = r"D:\NLP project\archive\data\000\a01-000u.png"
# Load image
img = Image.open(img_path)
# Show inside Jupyter
plt.imshow(img, cmap="gray")
plt.axis("off")
plt.title("Sample IAM Handwriting Image")
plt.show()
import pytesseract
```

```
from PIL import Image

# Make sure Tesseract path is set (same as Cell 2)

pytesseract.pytesseract.tesseract_cmd = r"C:\tesseract-ocr\tesseract.exe"

# OCR extraction

extracted_text = pytesseract.image_to_string(img)

print("Extracted Text:")

print(extracted_text)

!python -m spacy download en_core_web_sm

import spacy

nlp = spacy.load("en_core_web_sm")

doc = nlp(extracted_text)

print("Tokens:", [token.text for token in doc])

print("Lemmas:", [token.lemma_ for token in doc])

print("\nNamed Entities:")

for ent in doc.ents:

    print(ent.text, "->", ent.label_)

import os

from PIL import Image

import pytesseract

# Folder path

folder_path = r"D:\NLP project\archive\data\000"

# Collect only PNG files

files = [f for f in os.listdir(folder_path) if f.lower().endswith(".png")]

files = sorted(files)[:5]   # first 5, sorted for consistency

ocr_results = {}

for f in files:

    img_path = os.path.join(folder_path, f)

    try:

        img = Image.open(img_path)
```

```
        # Preprocess: convert to grayscale for better OCR
        img = img.convert("L")
        text = pytesseract.image_to_string(img)
        ocr_results[f] = text.strip()
    except Exception as e:
        ocr_results[f] = f"Error: {e}"
# Show results
print("OCR Results (first 5 images):")
for k,v in ocr_results.items():
    print(f"\n{k} -> {v}")
from jiwer import wer, cer
# Example OCR output (noisy)
ocr_text = """A MOVE to stop Mr. Gaitskell from nominating any more Labour life Peers is to
be made at a meeting of Labour M Ps tomorrow. Mr. Michael Foot has put down
a resolution on the subject and he is to be backed by Mr. Will Griffiths, M P for
Manchester Exchange."""
# Example Ground Truth (cleaned manually from IAM transcripts or by yourself)
ground_truth = """A MOVE to stop Mr. Gaitskell from nominating any more Labour life Peers is to
be made at a meeting of Labour MPs tomorrow. Mr. Michael Foot has put down
a resolution on the subject and he is to be backed by Mr. Will Griffiths, MP for
Manchester Exchange."""
# WER & CER
wer_score = wer(ground_truth, ocr_text)
cer_score = cer(ground_truth, ocr_text)
print("WER:", wer_score)
print("CER:", cer_score)
```

```
# Lemmatize OCR output
doc = nlp(ocr_text)
ocr_lemmatized = " ".join([token.lemma_ for token in doc])
# WER/CER after NLP cleanup
wer_nlp = wer(ground_truth, ocr_lemmatized)
cer_nlp = cer(ground_truth, ocr_lemmatized)
print("\nWER before NLP:", wer_score)
print("CER before NLP:", cer_score)
print("\nWER after NLP:", wer_nlp)
print("CER after NLP:", cer_nlp)
# Lemmatize OCR output
doc = nlp(ocr_text)
ocr_lemmatized = " ".join([token.lemma_ for token in doc])
# WER/CER after NLP cleanup
wer_nlp = wer(ground_truth, ocr_lemmatized)
cer_nlp = cer(ground_truth, ocr_lemmatized)
print("\nWER before NLP:", wer_score)
print("CER before NLP:", cer_score)
print("\nWER after NLP:", wer_nlp)
print("CER after NLP:", cer_nlp)
import pandas as pd
import matplotlib.pyplot as plt
results = pd.DataFrame({
    "Method": ["OCR Raw", "OCR + NLP"],
    "WER": [wer_score, wer_nlp],
    "CER": [cer_score, cer_nlp]
})
print(results)
results.set_index("Method").plot(kind="bar", figsize=(6,4))
plt.title("Error Rates: OCR vs OCR+NLP")
```

```
plt.ylabel("Error Rate")
plt.xticks(rotation=0)
plt.grid(axis="y", linestyle="--", alpha=0.6)
plt.show()
from spellchecker import SpellChecker
spell = SpellChecker()
def clean_text(text):
    words = text.split()
    corrected = [spell.correction(w) if spell.correction(w) else w for
w in words]
    return " ".join(corrected)
ocr_corrected = clean_text(ocr_text)
# Re-check error rates
wer_corrected = wer(ground_truth, ocr_corrected)
cer_corrected = cer(ground_truth, ocr_corrected)
print("WER after Spell Correction:", wer_corrected)
print("CER after Spell Correction:", cer_corrected)
results = pd.DataFrame({
    "Method": ["OCR Raw", "OCR + NLP", "OCR + SpellCorrect"],
    "WER": [wer_score, wer_nlp, wer_corrected],
    "CER": [cer_score, cer_nlp, cer_corrected]
})
print(results)
results.set_index("Method").plot(kind="bar", figsize=(7,4))
plt.title("Error Rates: OCR vs NLP vs SpellCorrect")
plt.ylabel("Error Rate")
plt.xticks(rotation=0)
plt.grid(axis="y", linestyle="--", alpha=0.6)
plt.show()
def run_ocr_with_settings(image_path, psm=6, oem=3):
    config = f'--psm {psm} --oem {oem}'
```

```
    return          pytesseract.image_to_string(Image.open(image_path),
config=config)
sample_image = os.path.join(folder_path, "a01-000u.png")


# Try different combinations
ocr_psm6 = run_ocr_with_settings(sample_image, psm=6, oem=3)
ocr_psm11 = run_ocr_with_settings(sample_image, psm=11, oem=3)
print("OCR with PSM 6:", ocr_psm6.strip())
print("OCR with PSM 11:", ocr_psm11.strip())
wer_psm6 = wer(ground_truth, ocr_psm6)
cer_psm6 = cer(ground_truth, ocr_psm6)
wer_psm11 = wer(ground_truth, ocr_psm11)
cer_psm11 = cer(ground_truth, ocr_psm11)
results = pd.DataFrame({
    "Method": ["OCR Raw", "OCR + NLP", "OCR + SpellCorrect", "OCR PSM6",
"OCR PSM11"],
    "WER": [wer_score, wer_nlp, wer_corrected, wer_psm6, wer_psm11],
    "CER": [cer_score, cer_nlp, cer_corrected, cer_psm6, cer_psm11]
})
print(results)
results.set_index("Method").plot(kind="bar", figsize=(8,4))
plt.title("OCR Settings Comparison")
plt.ylabel("Error Rate")
plt.xticks(rotation=30)
plt.grid(axis="y", linestyle="--", alpha=0.6)
plt.show()
import glob
from PIL import Image
# Path to dataset
dataset_path = r"D:\NLP project\archive\data"
# List of writer folders (000, 001, …)
```

```
writer_folders = sorted(glob.glob(dataset_path + "/*"))
print(f"Total writer folders: {len(writer_folders)}")

def batch_ocr(image_paths, psm=6, oem=3):
    texts = []
    config = f'--psm {psm} --oem {oem}'
    for img_path in image_paths:
        try:
            text   =   pytesseract.image_to_string(Image.open(img_path),
config=config)
            texts.append((img_path, text))
        except Exception as e:
            print(f"Error processing {img_path}: {e}")
            texts.append((img_path, ""))
    return texts
# Take first 2 folders for testing (for speed)
sample_folders = writer_folders[0:2]
all_images = []
for folder in sample_folders:
    all_images.extend(glob.glob(folder + "/*.png"))
# Run OCR on first 20 images
ocr_results = batch_ocr(all_images[:20], psm=6, oem=3)
print(f"Processed {len(ocr_results)} images")
def evaluate_batch(results, ground_truths):
    wer_list, cer_list = [], []
    for (img_path, ocr_text), gt in zip(results, ground_truths):
        if len(gt.strip()) == 0:  # Skip empty GT
            continue
        wer_list.append(wer(gt, ocr_text))
        cer_list.append(cer(gt, ocr_text))
    if wer_list:  # avoid division by zero
```

```
        return np.mean(wer_list), np.mean(cer_list)
    else:
        return None, None
avg_wer, avg_cer = evaluate_batch(ocr_results, ground_truths)
print(f"Average WER: {avg_wer}, Average CER: {avg_cer}")
# Example results summary (replace with your actual WER/CER values)
results_summary = [
    ("OCR Raw", 0.086957, 0.007874),
    ("OCR + NLP", 0.521739, 0.114173)
]
# Create DataFrame
import pandas as pd
df_summary = pd.DataFrame(results_summary, columns=["Method", "WER",
"CER"])
print(df_summary)
import matplotlib.pyplot as plt
# Ensure numeric types
df_summary["WER"] = pd.to_numeric(df_summary["WER"], errors="coerce")
df_summary["CER"] = pd.to_numeric(df_summary["CER"], errors="coerce")
# Drop rows where WER/CER are NaN
df_summary = df_summary.dropna(subset=["WER", "CER"])
# Now plot
df_summary.set_index("Method")[["WER", "CER"]].plot(kind="bar",
figsize=(8,4))
plt.title("Average OCR Performance on Dataset")
plt.ylabel("Error Rate")
plt.show()
# Numerical comparison summary
print("=== Comparative Results ===")
for _, row in df_summary.iterrows():
```

```
    print(f"{row['Method']}:                    WER={row['WER']:.4f},
CER={row['CER']:.4f}")
# Identify best performing method
best_method = df_summary.loc[df_summary["WER"].idxmin()]
print("\nBest Method (lowest WER):")
print(best_method)
import cv2
data_dir = r"D:\NLP project\archive\data\000"
# Pick some random images from IAM dataset
sample_images = [
    os.path.join(data_dir, "000", "a01-000u.png"),
    os.path.join(data_dir, "000", "a01-003u.png"),
    os.path.join(data_dir, "000", "a01-007u.png")
]
def crnn_predict(image_path, model):
    # Load and preprocess
    img = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)
    img = cv2.resize(img, (128, 32)) / 255.0
    img = np.expand_dims(img, axis=(0, -1))  # shape: (1, H, W, 1)
    # Predict
    preds = model.predict(img)
    pred_text = decode_batch(preds)[0]  # decode_batch from earlier
    return pred_text
# Compare OCR vs CRNN
for img_path in sample_images:
    ocr_text = pytesseract.image_to_string(Image.open(img_path))
    crnn_text = crnn_predict(img_path, crnn_model)
    print(f"\nImage: {os.path.basename(img_path)}")
    print(f"OCR (Tesseract): {ocr_text.strip()}")
    print(f"CRNN Prediction: {crnn_text.strip()}")
import torch
```

```
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
import torchvision.transforms as transforms
from PIL import Image
# ------------------------
# Dataset for OCR training
# ------------------------
class IAMDataset(Dataset):
    def __init__(self, image_paths, labels, transform=None):
        self.image_paths = image_paths
        self.labels = labels
        self.transform = transform
    def __len__(self):
        return len(self.image_paths)
    def __getitem__(self, idx):
        img   =   Image.open(self.image_paths[idx]).convert("L")      #
grayscale
        if self.transform:
            img = self.transform(img)
        label = self.labels[idx]
        return img, label
# Example transform (resize + tensor)
transform = transforms.Compose([
    transforms.Resize((32, 128)),
    transforms.ToTensor(),
])
# For now, fake labels (later connect real IAM GT)
train_dataset = IAMDataset(
    [img for img, _ in ocr_results[:100]],  # first 100 samples
    ["hello"] * 100,  # placeholder labels
```

```
    transform=transform
)
train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True)
# ------------------------
# CRNN Model
# ------------------------
class CRNN(nn.Module):
    def __init__(self, img_h=32, num_classes=100):   # num_classes = charset size
        super(CRNN, self).__init__()
        self.cnn = nn.Sequential(
            nn.Conv2d(1, 64, 3, 1, 1), nn.ReLU(), nn.MaxPool2d(2,2),
            nn.Conv2d(64, 128, 3, 1, 1), nn.ReLU(), nn.MaxPool2d(2,2),
        )
        self.rnn = nn.LSTM(128*8, 256, bidirectional=True, num_layers=2, batch_first=True)
        self.fc = nn.Linear(512, num_classes)
    def forward(self, x):
        x = self.cnn(x)  # (B, C, H, W)
        b, c, h, w = x.size()
        x = x.permute(0, 3, 1, 2).contiguous().view(b, w, c*h)  # (B, W, C*H)
        x, _ = self.rnn(x)
        x = self.fc(x)
return x  # (B, W, num_classes)
# ------------------------
# Initialize Model
# ------------------------
device = "cuda" if torch.cuda.is_available() else "cpu"
model = CRNN(img_h=32, num_classes=100).to(device)
print("CRNN model initialized on", device)
```

```
# ------------------------
# CTC Loss & Optimizer
# ------------------------
ctc_loss = nn.CTCLoss(blank=0)  # "0" reserved for CTC blank
optimizer = optim.Adam(model.parameters(), lr=1e-3)
# Example character set (dummy for now: a-z + space)
charset = ["<BLANK>"] + list("abcdefghijklmnopqrstuvwxyz ")
char_to_idx = {c: i for i, c in enumerate(charset)}
def text_to_labels(text):
    return [char_to_idx[c] for c in text if c in char_to_idx]
# ------------------------
# Training Loop (1 epoch)
# ------------------------
for epoch in range(1):
    model.train()
    epoch_loss = 0
    for imgs, texts in train_loader:
        imgs = imgs.to(device)
        # Convert text to label sequences
        labels = [torch.tensor(text_to_labels(t), dtype=torch.long) for
t in texts]
        label_lengths   =   torch.tensor([len(l)   for   l   in   labels],
dtype=torch.long)
        labels = torch.cat(labels)  # flatten
        # Forward pass
        logits = model(imgs)  # (B, W, num_classes)
        log_probs  =  logits.log_softmax(2).permute(1,  0,  2)   #  (W,  B,
num_classes)
        input_lengths        =        torch.full(size=(logits.size(0),),
fill_value=logits.size(1), dtype=torch.long)
        # CTC Loss
        loss = ctc_loss(log_probs, labels, input_lengths, label_lengths)
```

```
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        epoch_loss += loss.item()
    print(f"Epoch {epoch+1}, Loss: {epoch_loss/len(train_loader):.4f}")
```