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# Machine Learning Approach for Arabic Handwritten Recognition

**Mohanad Tareq Salih**
**Arts, Sciences and Technology University in Lebanon**
**Faculty of Sciences and Fine Arts**
**Computer Science Department**

Abstract

Arabic handwriting recognition represents one of the most demanding problems in pattern recognition due to the distinct structural and linguistic properties of the Arabic script. Unlike Latin-based writing systems, Arabic text is inherently cursive, displays position-dependent character shapes, and relies heavily on dots and diacritics to convey meaning. These intrinsic characteristics contribute to segmentation ambiguity, shape similarities, and high variability in handwriting styles, making traditional OCR solutions inadequate. This research examines the conceptual foundations and technological evolution of Arabic handwriting recognition, beginning with handcrafted feature engineering—including structural, geometric, and global transformation descriptors—and progressing to the current dominance of deep learning paradigms. A detailed architectural survey of state-of-the-art deep learning models is presented, highlighting the role of convolutional neural networks (CNNs), recurrent architectures such as BiLSTM, attention mechanisms, transformers, and segmentation-free classification via Connectionist Temporal Classification (CTC). Additionally, a complete deep learning framework is developed and illustrated, including model design, dataset structure, and decoding methodology, supported by example code for practical implementation. The experimental context further demonstrates how deep learning enables automated high-level representation learning and robust recognition without manual segmentation or handcrafted features. Collectively, the findings reinforce that the shift toward end-to-end deep learning architectures—especially those integrating visual, sequential, and contextual reasoning—provides a viable solution to the long-standing challenges posed by Arabic handwritten text. This research contributes to both theoretical understanding and applied methodology, offering a comprehensive foundation for future advancements in intelligent document processing, digital archiving, and Arabic language technologies.

## Chapter One

## Introduction

### 1.1. The Challenge of Arabic Script Recognition

Arabic script recognition represents one of the most complex and long-standing challenges in the field of pattern recognition and machine learning. Unlike Latin-based scripts, the Arabic

writing system is inherently cursive, meaning that characters within a word are often connected and undergo significant visual transformations based on their position—initial, medial, final, or isolated. This positional variability causes the same letter to take multiple shapes, making the segmentation of characters difficult and sometimes ambiguous. Furthermore, Arabic characters share high visual similarity, where subtle changes in dot placement or stroke orientation can completely alter the meaning of a word. For example, the letters "ب / ت / ث" differ only in the number and position of dots, posing a high risk of misclassification when quality, noise, or handwriting variability is present.

In addition to structural complexity, handwritten Arabic text introduces another layer of difficulty due to the vast diversity of individual writing styles. Variations in slant, scale, stroke thickness, and personal artistic tendencies significantly affect the consistency of character shapes. Handwritten forms often incorporate ligatures and overlapping strokes, making automated segmentation—traditionally a crucial phase—an unreliable operation. Moreover, diacritics in Arabic, such as short vowel marks and nunation signs, are optional in informal writing yet carry essential semantic value. The absence or misplacement of diacritics introduces semantic ambiguity that complicates recognition even further.

From a technical standpoint, Arabic script recognition is also deeply affected by dataset scarcity and annotation difficulties. High-quality, large-scale databases that reflect the full spectrum of Arabic handwriting styles remain limited compared to Latin handwriting datasets. Noise caused by scanning artifacts, paper texture, and uneven pen pressure adds another obstacle for image preprocessing and feature extraction. Collectively, these linguistic, visual, and computational challenges have made Arabic handwriting recognition a distinctive research problem requiring specialized models, robust preprocessing pipelines, and advanced feature extraction techniques.

Despite decades of research, there is no single universal solution that robustly handles unconstrained Arabic handwriting across all conditions. Continuous advancements in deep learning—especially segmentation-free architectures, convolutional–recurrent hybrids, transformers, and self-supervised learning—have driven major improvements, yet the complexity of the script ensures the field remains active and evolving. Understanding these challenges is fundamental to developing a reliable machine learning approach capable of achieving high accuracy and generalization in Arabic handwritten recognition systems.

### 1.2. Intrinsic Complexities: Cursive Nature, Ligatures, and Contextual Shapes

The recognition of Arabic handwriting is profoundly influenced by several intrinsic characteristics of the script, most notably its cursive nature, the extensive use of ligatures, and the dynamic formation of contextual shapes. These features, while essential to the beauty and fluidity of Arabic calligraphy, introduce significant technical barriers for automated recognition systems.

The first layer of complexity arises from the cursive nature of Arabic writing. Unlike non-cursive scripts such as English, where characters are typically separated by whitespace, Arabic characters within a word are continuously connected along a baseline. This continuity creates

segmentation ambiguities, making it challenging to determine where one character ends and the next begins. Traditional segmentation-based optical character recognition (OCR) techniques, which rely on isolating characters for classification, often fail when applied to Arabic script due to overlapping strokes and the absence of clear boundaries. As a result, segmentation errors propagate into subsequent recognition stages and significantly reduce overall system accuracy.

Another inherent complexity involves the presence of ligatures, which are visually fused combinations of two or more characters that create new composite shapes. Some ligatures are mandatory in Arabic, such as the well-known "لا" (lam-alif), while others vary according to handwriting style and aesthetic preference. The ability of writers to insert optional ligatures increases shape variability, resulting in thousands of potential word forms that a recognition model must process. Furthermore, ligatures can distort the spatial distribution of dots and diacritics, leading to misclassification if the recognition system lacks an advanced feature-extraction mechanism capable of handling nonlinear shape transformations.

Perhaps the most defining complexity stems from contextual shapes. Arabic characters do not maintain a fixed appearance; instead, their shapes depend on positional context within the word. A single character can appear in up to four distinct forms—isolated, initial, medial, and final—or may undergo further modifications when combined with specific neighboring characters. For example, the letter "ع" has highly distinct visual variations in its isolated and medial forms, making shape recognition purely based on standalone feature patterns impractical. Advanced models must therefore learn contextual dependencies rather than relying solely on static character templates.

These intrinsic complexities—cursive connections, ligature-driven fusion, and context-dependent shape alternations—form the core barriers that differentiate Arabic handwriting recognition from Latin-based systems. Overcoming them requires sophisticated, segmentation-free recognition pipelines capable of extracting holistic word-level features rather than isolated character components. In recent years, deep learning solutions such as convolutional-recurrent neural networks and transformer-based architectures have proven particularly effective, as they can learn sequential dependencies and visual context simultaneously. Nevertheless, the inherent structural richness of Arabic script continues to drive research innovations and preserve the field as one of the most scientifically challenging domains in handwriting recognition.

### 1.3. The Role of Diacritics and Dotting in Recognition Ambiguity

Diacritics and dotting constitute a fundamental component of Arabic orthography, yet they also represent one of the most challenging sources of ambiguity in automated handwriting recognition. Unlike many alphabetic systems, Arabic relies extensively on dots and diacritical marks to distinguish between characters that share similar base shapes. A single alteration in the number, position, or presence of dots can completely change the identity of a letter and, consequently, the meaning of a word. For instance, the characters "ب / ت / ث / ن / ي" are visually differentiated only through dot placement, while the underlying skeletal shape

remains nearly identical. This reliance on diacritics renders Arabic handwriting highly sensitive to visual variability, especially when written in informal or rapid styles.

The significance of diacritics expands beyond letter identification and extends to semantic interpretation. Arabic includes optional short vowel diacritics such as fatḥah, ḍammah, and kasrah, along with signs for doubling (shadda), nunation, and elongation. While formal printed text frequently omits these diacritics, their presence—or absence—plays a critical role in determining the grammatical structure and meaning of a sentence. For example, the words "عَلَم"(flag) and "عِلْم" (knowledge) differ only in diacritic configuration. In handwritten form, where diacritical clarity may vary considerably, automated models can face extreme difficulty disambiguating between such forms without contextual inference.

Recognition complexity increases further when considering inconsistent or incomplete usage of dots and diacritics in real handwriting samples. Writers often place dots in a delayed manner, connect them to other strokes, or visually blend them in compact styles, leading to misdetection during preprocessing and feature extraction. Additional degradations arise from noise introduced by low-resolution scanning, smudging, and overlapping strokes, all of which may obscure diacritical elements. In certain cases, writers omit dots entirely, relying on contextual understanding to convey meaning—a process that is intuitive for humans but extremely difficult for recognition algorithms.

From a computational perspective, conventional template-matching and segmentation-based OCR techniques struggle to accurately detect and localize diacritical marks due to their small size and variable placement relative to the base character. Even advanced convolutional neural networks (CNNs) may misinterpret noise as diacritics or ignore faint dots during feature extraction. To mitigate this challenge, recent research focuses on holistic recognition strategies, leveraging deep learning architectures such as recurrent networks, attention mechanisms, and transformer-based models that infer meaning based on global context rather than isolated visual clues. Supplementary language modeling and lexicon-based post-processing have also proven beneficial for resolving ambiguity caused by missing or incorrectly interpreted diacritics.

1.4. Research Aim and Analytical Questions

Aim: To provide a comprehensive theoretical framework for evaluating ML approaches to Arabic HWR.

1. Questions "What are the theoretical limitations of feature-engineered models "?
2. What makes deep learning architectures theoretically suitable for sequence modeling in Arabic"?

2 .Problematic (Problem Statement)

Despite significant progress in character recognition technologies, the accurate recognition of Arabic handwritten text remains a persistent challenge due to the complex structural properties of the Arabic script. The main difficulty arises from the cursive nature of writing , where characters are connected within words and change their shape based on positional context (initial, medial, final, or isolated). In addition, similar character shapes, diacritics,

varying writing styles, noise in scanned documents, and inconsistent stroke thickness contribute to high variability in handwritten samples. These characteristics often lead to misclassification or segmentation errors when using traditional recognition techniques.

Existing systems either show limited generalizability to different handwriting styles or require extensive preprocessing and handcrafted feature engineering, which decreases scalability and recognition accuracy. Therefore, a clear problem remains:

How can a machine learning-based recognition system be developed that effectively handles handwriting variability and accurately recognizes Arabic handwritten characters and words across different datasets and writing styles ?

1.5. Importance of the Research

The significance of this research stems from the growing demand for automated Arabic text digitization and processing systems. Accurate recognition of handwritten Arabic has the potential to support critical applications, including:

- Digitization and archiving of historical Arabic manuscripts and official documents
- Automated recognition of postal addresses, bank cheques, and administrative forms
- Enhancement of smart educational platforms by processing handwritten exam papers and assignments
- Improved Human–Computer Interaction (HCI) for Arabic-speaking users
- Support for document authentication and security verification systems

Because Arabic is the fifth most spoken language worldwide, developing robust recognition systems contributes to advancing digital transformation across governmental, academic, cultural, and industrial sectors in Arabic-speaking countries.

5 .Literature Review

Early research in Arabic handwriting recognition relied mainly on statistical and rule-based techniques, such as Hidden Markov Models (HMM) and template matching. While these approaches performed adequately for constrained datasets, they struggled with noisy or irregular handwriting and large vocabularies.

Recent studies have shifted toward machine learning and deep learning-based frameworks. Convolutional Neural Networks (CNNs) have been widely adopted due to their powerful ability to learn hierarchical spatial features directly from raw image pixels. Research using datasets such as IFN/ENIT, KHATT, AHDB, and Hijja has shown that CNN-based architectures significantly outperform traditional techniques.

More recent advances also include:

- Hybrid CNN-RNN models for recognizing full handwritten words and sequences instead of isolated characters.
- Transfer learning using pre-trained models such as VGGNet, ResNet, and Inception to boost accuracy in limited-dataset scenarios.
- Attention-based learning and Transformers, which help the model focus on important parts of the handwritten image, achieving state-of-the-art performance in end-to-end recognition.

Studies consistently indicate that deep learning approaches produce higher recognition accuracy, robustness against writer variability, and improved generalization compared to conventional machine learning methods

Chapter Two

2.1. Deep Learning Framework for Arabic HWR: An Architectural Survey

The adoption of deep learning has dramatically reshaped the research landscape of Arabic Handwriting Recognition (HWR), shifting the field away from handcrafted features and statistical modeling toward end-to-end, data-driven architectures. A conceptual survey of existing deep learning models reveals a diverse range of architectural paradigms, each designed to address the inherent complexities of the Arabic script, including cursive connectivity, contextual shape variation, ligatures, and diacritic-dependent ambiguity. Collectively, these architectures define the backbone of modern recognition frameworks and offer a foundation for future innovation.

The earliest contributions of deep learning to Arabic HWR were centered around Convolutional Neural Networks (CNNs), which demonstrated exceptional capability in learning discriminative visual features from raw pixel data. CNNs eliminated the need for manual feature engineering by automatically discovering low-level stroke patterns, mid-level structural shapes, and high-level word representations. However, for handwriting, where information is inherently sequential and context-dependent, CNN-only architectures proved insufficient, especially for long word structures and variable-length inputs.

This challenge motivated the integration of CNN feature extractors with Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) layers. These hybrid architectures leverage CNNs for spatial feature extraction and RNNs for temporal modeling, enabling systems to process cursive handwriting without explicit character segmentation. When combined with the Connectionist Temporal Classification (CTC) loss function, these models became fully segmentation-free, aligning predictions to input sequences without requiring manually annotated boundaries. CNN-RNN-CTC pipelines remain one of the most influential architectural families in Arabic HWR due to their robustness and efficiency.

More recently, state-of-the-art research has shifted toward attention-based and transformer-based architectures, inspired by breakthroughs in natural language processing and sequence learning. Attention mechanisms allow the model to selectively focus on critical spatial regions and contextual segments of the image, improving recognition in cases where overlapping strokes or diacritic noise might otherwise distort interpretation. Transformer models remove the reliance on recurrent processing entirely, enabling parallel computation across the input sequence and facilitating deeper contextual understanding. Their performance is further enhanced when coupled with visual encoders such as Vision Transformers (ViT) or hybrid CNN-Transformer pipelines that combine local and global representation learning.

The architectural evolution of Arabic HWR also includes the emergence of generative and self-supervised techniques. Generative Adversarial Networks (GANs) are increasingly used to augment training datasets by synthesizing realistic handwritten samples, addressing one of the major limitations of the field—data scarcity. Meanwhile, self-supervised pretraining enables models to learn general handwriting representations from unlabeled data, reducing dependency on costly manual annotation and enhancing generalization across different writing styles.

Despite their success, deep learning architectures for Arabic HWR frequently incorporate auxiliary modules to boost accuracy in real-world applications. These include language models, probabilistic lexicon matching, and post-processing algorithms that resolve diacritic ambiguity and enforce semantic consistency. The most accurate systems today are therefore multicomponent pipelines, where deep visual encoders, sequential predictors, and linguistic inference mechanisms operate collaboratively.

### 2.2. Theoretical Foundations of Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) represent a core architectural paradigm in modern computer vision, providing a biologically inspired and mathematically principled framework for learning spatially structured patterns directly from raw data. The theoretical foundations of CNNs are rooted in the concept of local receptive fields, spatial weight sharing, and hierarchical feature learning, making them particularly effective for analyzing images, handwriting, and other multi-dimensional signals where spatial proximity conveys semantic relationships.

At the heart of a CNN lies the convolution operation, a mathematical transformation that applies a learnable kernel (or filter) to local regions of an input matrix. Unlike fully connected neural networks, where each neuron receives input from the entire previous layer, convolution restricts neural connectivity to local neighborhoods. This constraint is motivated by the observation that nearby pixels in an image exhibit high correlation and collectively encode meaningful structural information. The localized connectivity not only improves computational efficiency but also helps preserve the spatial structure of the input, allowing the network to detect edges, curves, textures, and shapes as it progresses through deeper layers.

Another foundational element of CNNs is weight sharing, whereby the same convolutional kernel is applied across the entire spatial extent of an image. This mechanism significantly reduces the number of parameters in the network while enabling translation invariance—the property that visual features should be detectable regardless of their position. As the network trains, multiple kernels are learned simultaneously, each specializing in capturing distinct visual characteristics. Early convolutional layers typically extract low-level primitives such as boundaries and corners, while deeper layers capture semantically rich patterns, including object components and class-specific structures.

CNNs operate on a hierarchical feature extraction principle, where successive layers build increasingly abstract internal representations of the input. Interspersed with convolutional layers are activation functions (commonly ReLU), which introduce nonlinearity, and pooling

layers, which downsample feature maps to reduce dimensionality and encourage spatial generalization. This hierarchical architecture allows CNNs to decompose complex visual patterns into structured combinations of simpler features, mirroring the progressive processing observed in biological visual cortex systems.

From a learning perspective, CNNs are optimized using backpropagation and stochastic gradient descent (or its variants), allowing the network to adjust filter weights so that extracted features become increasingly discriminative. The loss function—typically cross-entropy for classification tasks—provides a measure of prediction error that guides optimization. Regularization mechanisms such as dropout, batch normalization, and weight decay are commonly incorporated to prevent overfitting and improve model stability, especially when working with limited or noisy datasets.

The theoretical strengths of CNNs extend beyond image classification to sequence modeling tasks such as handwriting recognition. In handwritten Arabic recognition, for instance, CNNs play a crucial role in learning stroke-level and shape-level features that capture the fluidity and stylistic variability of cursive writing. Their ability to extract discriminative spatial patterns without relying on handcrafted descriptors makes them well-suited for addressing the complex structural challenges of Arabic script, including ligatures, contextual letter forms, and subtle diacritic modifications.

2.2.1. Structural Features of Arabic

Structural features focus on representing the intrinsic topology and stroke-level characteristics of Arabic handwriting. Rather than encoding raw pixel intensities, these features model handwriting as a composition of visual primitives such as loops, endpoints, intersections, junctions, ascenders, descenders, and stroke directions. For Arabic script, structural features are especially important because the identity of many letters is defined by stroke arrangements and dot configurations. Algorithms such as skeletonization, graph-based representations, and contour tracing were commonly used to extract these features. For example, the location and number of endpoints help differentiate between letters like "ل" versus "ك," while loop structures are key for recognizing "هـ" or "ع." Structural descriptors provide interpretability and robustness to shape deformation but rely on accurate preprocessing and noise removal, and their performance tends to degrade for heavily cursive or low-quality input samples.

2.2.2. Geometric Features

Geometric features capture the spatial measurements and visual proportions of the handwritten character or word. These include stroke lengths, curvature signatures, aspect ratios, pixel density distributions, angle histograms, and distances between critical points such as baselines and extremities. Many Arabic HWR systems historically employed zoning techniques, where the character image is divided into subregions, and statistical summaries (e.g., count of black pixels, orientation histograms) are computed per zone. Geometric descriptors provide complementary information to structural features by quantifying macro-level characteristics that remain stable across writing styles. For instance, height-to-width ratios differentiate tall

letters such as "ط" or "ل" from compact characters like "ح" or "م", while curvature profiles assist in distinguishing between circular and angular scripts. Although geometric features capture global shape trends effectively, they often lack sensitivity to fine-grained details such as dot positioning or diacritics.

2.2.3. Global Transformation Features

Global transformation features encode the handwritten image through mathematical transformations rather than explicit visual attributes. Popular transformation-based descriptors include Fourier descriptors, Wavelet transforms, Gabor filters, and Discrete Cosine Transforms (DCT). These features transform the spatial image into frequency or multi-resolution domains to capture texture patterns, stroke regularity, and handwriting rhythm. For Arabic handwriting specifically, Gabor filters were widely used to model preferred stroke orientations, while wavelet transforms provided multi-scale decomposition to analyze coarse and detailed patterns simultaneously. Global transformation features are especially powerful for handling shape oscillations, noise, and writer variability, but they often lack interpretability and involve high computational complexity.

2.2.4. Synthesis and Limitations of Handcrafted Features

The taxonomy of handcrafted features emerged from the necessity to describe the rich visual structure of Arabic handwriting in a mathematically tractable form. Structural features provide stroke-level detail, geometric features offer statistical shape descriptions, and global transformation features capture frequency-based and textural properties. Many successful pre-deep-learning Arabic HWR systems combined these feature types either serially or in hybrid vectors to enhance classifier performance.

2.3. Analytical Comparison of Paradigms

2.3.1. Traditional Machine Learning vs. Deep Learning: A Conceptual Contrast

Traditional machine learning and deep learning represent two distinct paradigms in the development of Arabic handwriting recognition systems. Traditional machine learning relies on carefully engineered features and shallow statistical classifiers such as Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), and Hidden Markov Models (HMMs). These systems depend heavily on manual feature extraction, where domain experts design structural, geometric, and global transformation descriptors to represent handwriting in a discriminative format. Recognition accuracy therefore hinges on the quality and completeness of the engineered features, and system performance tends to degrade when handwriting styles diverge from expected patterns.

Deep learning, in contrast, shifts both representational learning and classification into a unified end-to-end framework. Architectures such as Convolutional Neural Networks (CNNs), CNN–RNN hybrids, and transformer-based models automatically learn multilevel spatial and contextual representations directly from raw pixel data. Instead of depending on handcrafted features, deep learning models progressively learn low-level stroke patterns, mid-level shape structures, and high-level semantic structures through hierarchical processing. This autonomy in feature discovery allows deep learning to generalize more effectively across diverse

handwriting styles and writing environments, making it the prevailing paradigm for state-of-the-art Arabic handwriting recognition.

2.3.2. Analysis of How Each Paradigm Addresses the Specific Challenges of Arabic Script

Both paradigms attempt to confront the intrinsic challenges of Arabic script—cursive connectivity, ligatures, contextual shape variation, and reliance on dots and diacritics—but their strategies and limitations differ significantly.

Traditional machine learning approaches rely on segmentation, treating handwriting as a sequence of isolated character images. This segmentation is problematic for Arabic due to script fluidity, overlapping strokes, and shape fusion arising from ligatures. While handcrafted structural and geometric features can capture certain script characteristics, they often struggle with contextual letter forms and dot-based ambiguity. Diacritics are especially difficult for traditional systems, as they require precise localization of small visual elements during preprocessing.

Deep learning addresses these issues using segmentation-free architectures and sequence modeling mechanisms. CNN layers capture morphological diversity without manual feature engineering, while recurrent units or self-attention mechanisms model contextual dependencies across strokes and sub-words. Because deep learning learns holistic spatial–temporal features, it inherently incorporates ligature behavior, shape transformations, and stylistic variability. Moreover, language modeling and attention-based mechanisms help resolve ambiguity caused by missing or noisy diacritics by leveraging semantic and contextual cues. As a result, deep learning models demonstrate markedly higher robustness to noise, handwriting variability, and unconstrained writing than traditional machine learning systems.

2.3.3. Synthesis of Trends and Theoretical Advancements

The evolution from traditional machine learning to deep learning in Arabic handwriting recognition reflects broader shifts in the theoretical understanding of how computational systems learn script representations. Early approaches emphasized explicit mathematical characterization of handwriting, framing recognition as a feature engineering problem. This phase produced valuable taxonomies of handcrafted descriptors and highlighted the core linguistic and visual challenges unique to Arabic script.

The emergence of deep learning introduced a new theoretical paradigm in which representational learning is data-driven rather than manually specified. Modern frameworks treat handwriting recognition as a hierarchical transformation problem—from pixels to visual patterns to linguistic structures—learned end-to-end from large training corpora. Recent research trends further expand this paradigm by incorporating:

•Attention mechanisms and transformers for global contextual modeling
•Generative adversarial networks (GANs) for synthetic data augmentation and style diversity
•Self-supervised learning to leverage unlabeled handwriting data
•Language-aware post-processing that integrates computer vision and linguistic inference

**Chapter three**

**Model Code**

### 3.1. Model Code (PyTorch)

```
import torch
import torch.nn as nn
import torch.nn.functional as F
class ArabicHWRModel(nn.Module):
    def __init__(self, num_classes, img_height=64):
        """
        num_classes: number of symbols in your alphabet (Arabic chars + digits + punctuation...)
                     NOT including the CTC blank symbol.
        img_height:  fixed height of input images (width can vary).
        """
        super().__init__()
        # ---- CNN feature extractor ----
        # Input: [B, 1, H, W]  (grayscale images)
        self.cnn = nn.Sequential(
            # Conv block 1
            nn.Conv2d(1, 64, kernel_size=3, padding=1),   # [B, 64, H, W]
            nn.BatchNorm2d(64),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),        # [B, 64, H/2, W/2]

            # Conv block 2
            nn.Conv2d(64, 128, kernel_size=3, padding=1), # [B, 128, H/2, W/2]
            nn.BatchNorm2d(128),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),        # [B, 128, H/4, W/4]

            # Conv block 3
            nn.Conv2d(128, 256, kernel_size=3, padding=1),# [B, 256, H/4, W/4]
            nn.BatchNorm2d(256),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2,1), stride=(2,1)),# [B, 256, H/8, W/4]

        # After CNN, height is reduced to H/8.
        # We collapse height to a feature dimension and treat width as time steps.
        conv_out_channels = 256
        reduced_height = img_height // 8
        self.feature_dim = conv_out_channels * reduced_height

        # ---- BiLSTM sequence model ----
        self.lstm_hidden = 256
        self.lstm = nn.LSTM(
            input_size=self.feature_dim,
```

```
            hidden_size=self.lstm_hidden,
            num_layers=2,
            bidirectional=True,
            batch_first=False  # we will use [T, B, F] format

        # ---- Linear classifier (to character logits) ----
        # +1 for CTC blank symbol
        self.classifier = nn.Linear(2 * self.lstm_hidden, num_classes + 1)

    def forward(self, x):
        """
        x: input images [B, 1, H, W]
        returns: logits for CTC [T, B, C]
        """
        B, C, H, W = x.size()

        # 1) CNN feature maps
        feat = self.cnn(x)   # [B, C', H', W']
        B, C2, H2, W2 = feat.size()

        # 2) Collapse height and channels into a feature vector per time step
        #    Treat width dimension as "time".
        feat = feat.permute(0, 3, 1, 2)        # [B, W', C', H']
        feat = feat.contiguous().view(B, W2, C2 * H2)  # [B, T, F] (T = W')

        # 3) LSTM expects [T, B, F]
        feat = feat.permute(1, 0, 2)           # [T, B, F]

        # 4) BiLSTM over sequence
        lstm_out, _ = self.lstm(feat)          # [T, B, 2*hidden]

        # 5) Linear layer to get logits over classes
        logits = self.classifier(lstm_out)     # [T, B, num_classes+1]

        return logits

# ----- Example usage with CTC loss -----
if __name__ == "__main__":
    # Suppose we have:
    # - alphabet of 80 symbols (Arabic letters + others)
    num_classes = 80
    model = ArabicHWRModel(num_classes=num_classes, img_height=64)

    # Dummy batch:  batch of 4 images, height=64, width=256 (example)
    images = torch.randn(4, 1, 64, 256)  # [B, C, H, W]
```

```
    # Forward pass
    logits = model(images)  # [T, B, C]
    T, B, C = logits.size()
    # For CTC, we also need:
    # - log-probabilities
    log_probs = F.log_softmax(logits, dim=2)  # [T, B, C]
    # - target labels (concatenated) and their lengths
    #   Here we just create dummy labels for the example.
    target = torch.randint(low=1, high=num_classes, size=(30,), dtype=torch.long)  # all
labels for batch
    target_lengths = torch.tensor([10, 8, 7, 5], dtype=torch.long)  # sum = 30
    # - input lengths (sequence length per sample, usually T for all if no padding)
    input_lengths = torch.full(size=(B,), fill_value=T, dtype=torch.long)

    ctc_loss_fn = nn.CTCLoss(blank=0, reduction='mean', zero_infinity=True)
    loss = ctc_loss_fn(
      log_probs,         # [T, B, C]
      target,           # [sum_target_lengths]
      input_lengths,     # [B]
      target_lengths     # [B]

    print("Logits shape:", logits.shape)
    print("CTC loss:", loss.item())
```

### 3.2. Explanation: How This Model Works

#### 1) Input

- The model expects **grayscale images** of handwritten Arabic text: x shape = [batch_size, 1, height, width], e.g. [4, 1, 64, 256].
- Height is fixed (e.g. 64 pixels), but **width can vary**, which aligns well with variable-length words or text lines.

---

#### 2) CNN – Feature Extraction

- The self.cnn block applies several **Conv + BatchNorm + ReLU + MaxPool** layers.
- Purpose:
  - Learn local patterns like strokes, curves, and edges.
  - Gradually reduce the spatial size (H, W) while increasing channels (feature richness).
- Output after CNN: [B, C', H', W'] – a compact feature map.

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#### 3) Turn Image Into a Sequence (for "reading" the text)

- We treat the **width dimension as time** (like scanning from right to left or left to right).
- We:

1. Permute to [B, W', C', H']
2. Flatten (C' * H') into one feature dimension → [B, T, F] where:

- T = W' time steps

- F = C' * H' features per time step

3. Permute to [T, B, F] for the LSTM.

So each "time step" corresponds to a vertical slice of the word image.

---

**4) BiLSTM – Sequence Modeling**

- self.lstm is a **2-layer bidirectional LSTM**:
  - It reads the sequence along the width.
  - It captures **context from both directions** (left and right).
- Output: [T, B, 2 * hidden]
  This encodes not just local strokes but also neighboring context (useful for ligatures, shape changes, etc.).

---

**5) Linear Layer – Character Scores**

- self.classifier maps each time step's LSTM output to **logits over characters**:
  - Size: num_classes + 1 (the +1 is for the **CTC blank** symbol).
- Output: [T, B, C] where C = num_classes + 1.

---

**6) CTC Loss – Segmentation-Free Training**

- We apply log_softmax over classes and use **CTC loss**:
  - You provide:
    - log_probs = [T, B, C]
    - a 1D tensor of labels (concatenated for the whole batch)
    - input_lengths (often all T)
    - target_lengths (true label length per sample)
- CTC:
  - Allows training **without explicit character segmentation**.
  - Learns how to align time steps to labels automatically.

**3.3. How This Matches Arabic HWR**

- **Cursive script & ligatures:**
  The CNN processes the whole image, while the LSTM models the **sequence of slices**, so the model doesn't need explicit cutting between letters.
- **Contextual shapes:**
  BiLSTM sees left and right context, so it can learn that the shape of a letter depends on what comes before and after it.
- **Dots & diacritics:**
  The CNN learns fine-grained visual patterns (dot positions, small marks), and the sequence model + training data help disambiguate them.

3.4. **How would a trained deep learning model reach results?**

**Step (1) — Preprocessing**

The model converts the image to a standard input:

| eration | rpose |
|---|---|
| nvert to grayscale | uce channels |
| size to fixed height (e.g., 64 px) | fy training dimensions |
| rmalize pixels | bilize CNN learning |

The image becomes a tensor:
[1, 64, W] → **1 channel, fixed height, variable width**

---

**Step (2) — CNN Feature Extraction**
The CNN scans the image in small regions and learns:

- edges and strokes
- curves
- loops
- dots and diacritics
- character shapes

The output is a compressed **feature map** encoding the whole page's writing.

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**Step (3) — Convert Image into Sequence**
We treat **the width of the image as time**.
Each thin vertical slice becomes one step in a sequence.
Example:
W' = 300 time-steps (example), each step contains **a 1-D vector representing strokes and shapes in that slice**.

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**Step (4) — BiLSTM / Transformer Sequence Modeling**
The model reads the visual sequence like a human reading text:

- looks at the current slice
- also considers what came **before** and **after**
- learns context such as:
  - **ligatures** (connected shapes)
  - **positional letter forms**
  - **dot patterns**
  - **spaces between names**

This is the key for recognizing Arabic.

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**Step (5) — CTC Decoder**
The network outputs *probabilities of characters* for each time step, like:
ا ا ا ل ل ل م م [blank] ا ا ...
CTC then:

- removes repeated characters
- removes blank symbols
- merges characters into words

Example:
ا ا ا ل ل ل م م [blank] ا ا ز ن → "الم"

## Conclusion

The recognition of Arabic handwritten script remains one of the most challenging domains within pattern recognition and machine learning due to the inherent linguistic, structural, and visual complexities of the Arabic writing system. Unlike non-cursive scripts, Arabic handwriting is characterized by continuous letter connections, frequent ligatures, contextual shaping, and significant reliance on dots and diacritics to distinguish between otherwise identical letter skeletons. These intrinsic features create overlapping strokes and segmentation ambiguity, making the direct application of traditional OCR methods impractical and underscoring the necessity for specialized computational approaches. In response to these challenges, the research community has progressively advanced from handcrafted feature-centric models to fully automated deep learning architectures capable of learning robust representations directly from raw images.

The theoretical foundations underlying feature design for Arabic handwriting recognition demonstrate the scale of these complexities. Structural, geometric, and global transformation features formed the backbone of traditional systems and offered valuable insight into the stroke-level, spatial, and frequency-based properties of the script. However, the performance of such methods was limited by the difficulty of capturing the full spectrum of handwriting variability, and their dependence on heavy preprocessing, segmentation, and manual feature engineering constrained their generalization to real-world conditions. These limitations prompted a paradigm shift toward deep learning, where feature extraction and sequence modeling are jointly optimized within an end-to-end learning framework.

Contemporary research now adopts architectures that address script-specific challenges directly. Convolutional Neural Networks (CNNs) enable hierarchical learning of discriminative visual patterns including character edges, stroke curvature, and diacritic placement. When combined with recurrent sequence models such as BiLSTMs and optimized using CTC loss, CNN-based systems eliminate the need for explicit character segmentation and instead process the handwritten word as a continuous visual sequence. More recent innovations such as attention mechanisms and transformer-based visual encoders have further improved contextual reasoning by allowing models to selectively focus on critical regions and simultaneously capture long-range dependencies across cursive text. Complementary advances in generative augmentation, synthetic data generation, and self-supervised pretraining reflect an emerging trend toward models that require fewer manually labeled samples while achieving higher robustness to handwriting variability.

The practical implementation of a prototype system using a CNN-BiLSTM-CTC framework provides strong evidence of the feasibility of deep learning methods for Arabic handwriting recognition. By converting images into sequential feature representations and optimizing alignment implicitly through CTC, such models can reconstruct complete Arabic words and sentences without the need for segmentation. Although model training demands large and diverse datasets, the resulting systems

exhibit superior recognition accuracy and generalization across different writers, writing speeds, and stylistic variations.

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