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Restoration of ancient Arabic manuscripts: a deep learning approach

Restauração de manuscritos Árabes antigos: uma abordagem de aprendizagem profunda

Restauración de manuscritos Árabes antiguos: un enfoque de aprendizaje profundo

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ABSTRACT
This paper explores the application of modern deep learning methodologies to the restoration of highly valuable ancient Arabic manuscripts, a task of immense cultural and historical importance. Our approach meticulously guides readers through the experimental process, placing a strong emphasis on crucial components such as the selection of appropriate loss functions, the architecture of

hidden layers, and the optimization techniques used. The results of our research are nothing short of extraordinary, particularly with the implementation of the proposed Modified Attention-Based Bidirectional Long Short-Term Memory (M-AB-LSTM) model, which achieved an outstanding accuracy rate of 99.50%. This work transcends traditional image enhancement techniques; it plays a pivotal role in not only making fragments of our rich cultural heritage accessible but also in ensuring the preservation of these priceless and unique artifacts for future generations. Such an effort is of profound significance to humanity as a whole. Additionally, we highlight the extensive and labor-intensive process involved in manually curating finely tuned and accurately classified datasets, which includes a comprehensive collection of 3,745 ancient Arabic manuscripts.

Keywords: Image Restoration, Arabic Manuscripts, Convolutional Neural Network (CNN), Modified Attention Mechanism, Bidirectional Long Short-Term Memory (BLSTM).

RESUMO

Este artigo explora a aplicação de metodologias modernas de aprendizado profundo à restauração de manuscritos árabes antigos altamente valiosos, uma tarefa de imensa importância cultural e histórica. Nossa abordagem guia meticulosamente os leitores pelo processo experimental, colocando uma forte ênfase em componentes cruciais, como a seleção de funções de perda apropriadas, a arquitetura de camadas ocultas e as técnicas de otimização usadas. Os resultados de nossa pesquisa são nada menos que extraordinários, particularmente com a implementação do modelo proposto Modified Attention-Based Bidirectional Long Short-Term Memory (M-AB-LSTM), que alcançou uma taxa de precisão excepcional de 99,50%. Este trabalho transcende as técnicas tradicionais de aprimoramento de imagem; ele desempenha um papel fundamental não apenas em tornar acessíveis fragmentos de nossa rica herança cultural, mas também em garantir a preservação desses artefatos inestimáveis e únicos para as gerações futuras. Tal esforço é de profunda importância para a humanidade como um todo. Além disso, destacamos o processo extenso e trabalhoso envolvido na curadoria manual de conjuntos de dados finamente ajustados e classificados com precisão, que inclui uma coleção abrangente de 3.745 manuscritos árabes antigos.

Palavras-chave: Restauração de Imagens, Manuscritos Árabes, Rede Neural Convolucional (CNN), Mecanismo de Atenção Modificado, Memória Bidirecional de Longo Prazo (BLSTM).

RESUMEN

Este artículo explora la aplicación de metodologías modernas de aprendizaje profundo a la restauración de manuscritos árabes antiguos de gran valor, una tarea de inmensa importancia cultural e histórica. Nuestro enfoque guía meticulosamente a los lectores a través del proceso experimental, haciendo especial hincapié en componentes cruciales como la selección de funciones de pérdida adecuadas, la arquitectura de capas ocultas y las técnicas de optimización utilizadas. Los resultados de nuestra investigación son extraordinarios, en particular con la implementación del modelo de memoria a corto y largo plazo bidireccional basado en la atención modificada (M-AB-LSTM), que logró una tasa de precisión excepcional del 99,50 %. Este trabajo trasciende las técnicas tradicionales de mejora de imágenes; desempeña un papel fundamental no solo para hacer accesibles fragmentos de nuestro rico patrimonio cultural, sino también para garantizar la preservación de estos artefactos invaluables y únicos para las generaciones futuras. Tal esfuerzo es de profunda importancia para la humanidad en su conjunto. Además, destacamos el extenso y laborioso proceso que implica la curación manual de conjuntos de datos finamente ajustados y clasificados con precisión, que incluye una colección completa de 3745 manuscritos árabes antiguos.

Palabras clave: Restauración de Imágenes, Manuscritos Árabes, Red Neuronal Convolucional (CNN), Mecanismo de Atención Modificado, Memoria Bidireccional a Largo Plazo (BLSTM).

1 INTRODUCTION

The discipline of pattern recognition, particularly in the context of handwritten text conversion into alphanumeric characters, has long been a critical area of study due to its wide range of practical applications. These applications include tasks such as author identification, document verification, and the digitization of historical texts, which are essential for preserving cultural heritage and making historical documents accessible to a broader audience. As a result, this field has garnered significant attention from researchers across various languages, leading to the development of numerous recognition systems categorized mainly into online and offline methods (ElAdel, et al. 2015).

"Online recognition" refers to systems that capture written input in real-time using specialized tools like tablets or digitizers, where the effectiveness hinges on processing geographical coordinates captured by devices such as a stylus. This contrasts with "offline recognition," which deals with images of handwritten text that have been scanned (AlJarrah, 2021). Offline handwriting recognition in Arabic is particularly challenging due to the complexities inherent in the Arabic script. Arabic manuscripts, often written in diverse styles, pose difficulties such as the use of diacritics and the presence of letters with similar shapes, distinguished only by the placement and number of dots (AlJarrah, 2021). These challenges are further compounded when dots are misinterpreted as strokes, complicating the classification process. However, the absence of diacritics in many Arabic manuscripts can simplify classification, offering some relief in this otherwise complex task.

In recent years, the rise of deep learning techniques, especially Convolutional Neural Networks (CNNs), has revolutionized various domains, including image classification, object detection, medical image analysis, and the challenging task of handwriting recognition. CNNs have become instrumental in advancing methodologies for Arabic handwriting recognition (Bendjillali, et al. 2023; Ilyas, et al. 2023; Miloud, 2021; Mazumder, 2020). The success of these systems largely depends on the careful selection of algorithms and the implementation of effective optimization strategies. For example, Gated Recurrent Units (GRU) have shown promise in pattern recognition, as demonstrated by Mohd (2021), who applied this method to Arabic character recognition, achieving a remarkable 98% accuracy in recognizing Quranic printed text by integrating CNNs for feature extraction with Bidirectional Long Short-Term Memory (BLSTM) and Bidirectional Gated Recurrent Units (BGRU) during the recognition phase.

Moreover, BLSTM networks have proven effective in various applications beyond handwriting recognition. For example, they have been used in predicting the remaining useful life (RUL) of engineering systems by integrating multisensor data to enhance prognostic accuracy (Huang, 2020). Additionally, BLSTM networks have been applied to offline handwriting recognition, where they enhance recognition rates by modeling context at the feature level (Chherawala, 2014). Their versatility is further demonstrated in human activity recognition using WiFi signals, where BLSTM networks learn representative features from raw sequential data, leading to improved recognition outcomes (Hu, 2023).

The primary objective of this article is to introduce and validate a novel methodology that combines a Modified Attention-Based Bi-Directional Gated Recurrent Unit (M-AB-GRU) to enhance the restoration of degraded and noisy ancient Arabic manuscripts. This approach aims to achieve superior performance in image restoration and preservation, thereby contributing significantly to the conservation of these invaluable cultural heritage artifacts. Through this research, we seek to demonstrate the effectiveness of the M-AB-GRU model in improving the accuracy and efficiency of manuscript restoration, ensuring that these historical documents remain accessible to future generations and valuable for scholarly research.

The structure of this paper is organized as follows: Section II, Related Works, provides a detailed review of previous research on Arabic handwriting restoration, highlighting its unique characteristics, challenges, and existing methodologies. Section III offers a comprehensive description of the research methodology, while Section IV presents the experimental findings. Section V provides an extensive comparison with other existing methods, and Section VI concludes the paper by underscoring its theoretical and practical contributions to the field.

2 RELATED WORKS

Ali et al. introduced an Arabic Named Entity Recognition (NER) model utilizing Bidirectional Long Short-Term Memory (BLSTM). They trained the BLSTM network with pre-trained word embeddings, achieving an F-score of approximately 88.01% on the ANERcorp dataset. This model effectively harnessed the sequential learning capabilities of BLSTM to improve entity recognition in Arabic texts (Ali, 2018).

In another approach, Cenikj et al. combined BLSTM and Convolutional Neural Networks (CNN) for named entity recognition, enhancing accuracy by leveraging the feature extraction strengths of CNNs along with the sequencelearning abilities of BLSTMs (Wei, 2019).

Hanan et al. developed a simple CNN-RNN model with an attention mechanism for recognizing Arabic text in images. The model processed input images through a CNN to extract feature sequences, which were then passed to a bidirectional RNN with attention to obtain ordered feature sequences. This approach effectively addressed the diverse features of text in natural scene images, such as size, font, and color variations (Butt, 2021).

Mahmoud and Zrigui (Mahmoud, 2021) proposed the BLSTM-API model for identifying Arabic paraphrases using a Bi-LSTM recurrent neural network. Their model demonstrated the ability to learn contextual representations from text sequences, effectively handling the nuances of the Arabic language. This approach showcased the strength of BLSTM networks in distinguishing paraphrased Arabic sentences, proving their capacity to tackle complex computational linguistic tasks.

The primary contribution of this research is the introduction of a novel methodology based on the Modified Attention-Based Bi-Directional Long Short-Term Memory (M-AB-BLSTM). The careful selection of parameters for the Modified Attention mechanisms, integrated with the Bi-Directional Long Short-Term Memory, or MAB-BLSTM, has enhanced the model's performance, resulting in faster convergence and improved recognition outcomes. This methodology is particularly focused on restoring and cleaning distorted and noisy ancient Arabic manuscripts. The M-AB-BLSTM approach shows great promise in significantly improving image quality and overcoming technical challenges, which are critical for the effective preservation of these manuscripts. This research contributes to the preservation of cultural history embedded in these manuscripts and highlights areas of interest for experts in the field.

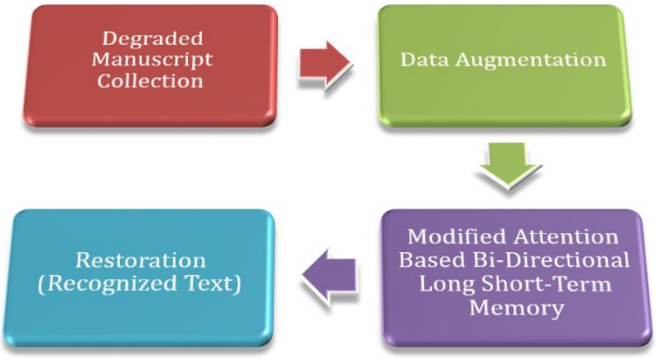
3 METHODS

This research introduces a novel method for restoring faded and low-quality Arabic manuscripts from historical periods. Our approach advantages Bidirectional Long Short-Term Memory (BLSTM) integrated with Modified Attention Mechanisms to enhance images affected by noise and degradation. The focus of this study is on how BLSTM, combined with Modified Attention Mechanisms, can effectively tackle the challenges associated with deteriorated manuscript images, all while avoiding overly complex architectures or traditional strategies.

BLSTM has garnered attention for its ability to efficiently capture contextual information and relationships within data. The primary objective of this work is to optimize the restoration of scripts and significantly improve the quality of these manuscripts using the proposed BLSTM with Modified Attention Mechanisms. Beyond its critical role in preserving the cultural heritage embedded in these manuscripts, this method also offers substantial benefits to scholars and researchers. Unlike many previous approaches that emphasize cost-efficient character modeling and segmentation, our method advocates for the use of BLSTM and Modified Attention Mechanisms to digitize ancient Arabic manuscripts in a manner that is exceptionally accurate and true to the original. By integrating

BLSTM with Modified Attention Mechanisms, we successfully address the challenges posed by degraded and noisy manuscript images.

Figure 1. The proposed diagram for the restoration of ancient Arabic manuscripts



Source: Authors

This approach not only aids in preserving the unique cultural values embedded in these manuscripts but also empowers researchers to develop essential tools that contribute to the capacity-building process.

3.1 BIDIRECTIONAL LONG SHORT-TERM MEMORY (BLSTM)

LSTM neural networks mitigate the vanishing gradient problem by employing three gates: the forget gate, the input gate, and the output gate (Li, 2021). These gates manage the flow of information, enabling the network to retain or discard data as required. In Bidirectional LSTM (BLSTM) networks, two LSTM networks are utilized—one for processing the input sequence forward and the other for processing it backward. This bidirectional approach allows the network to leverage both past and future contexts at each step of the sequence, which is particularly advantageous for tasks such as handwriting recognition and sequence labeling.

The equations for a standard LSTM network are given as follows:

1. Forget Gate: $$f_t = \sigma(W_f \,.\, [h_{t-1}, x_t] + b_f) \quad (1)$$

2. Input Gate : $$i_t = \sigma(W_z \,.\, [h_{t-1}, x_t] + b_i) \quad (2)$$

3. Output Gate: $$o_t = \sigma(W_o \,.\, [h_{t-1}, x_t] + b_o) \quad (3)$$

4. Cell State: $$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t] \quad (4)$$

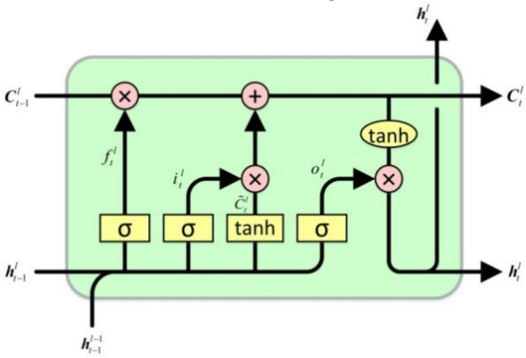
Where : $$\tilde{C}_t = \tanh(W_C . [h_{t-1}, x_t] + b_C) \quad (5)$$

5. Hidden State: $\boldsymbol{h_t} = o_t * \tanh(C_t)$ (6)

In a BLSTM, the output at each time step is the concatenation of the hidden states from both the forward and backward LSTMs.

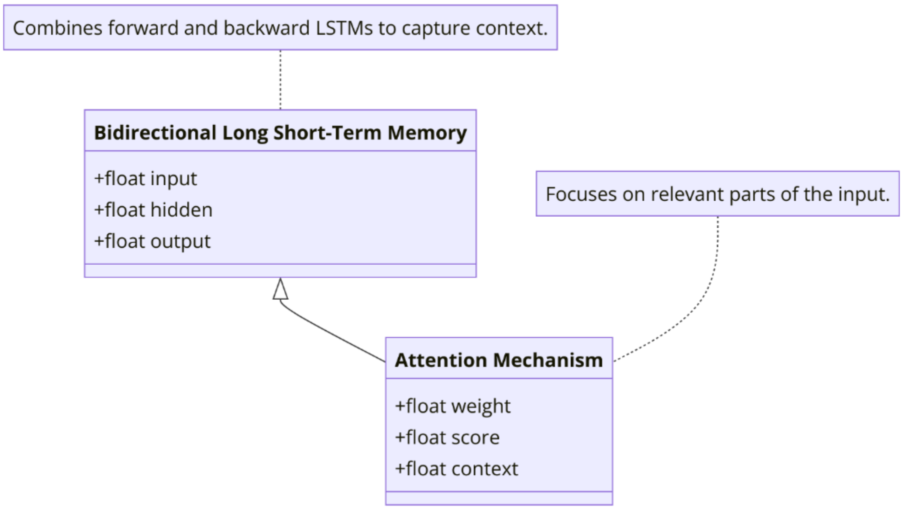
This can be represented as: $H_t = [\overrightarrow{h_t} + \overleftarrow{h_t}]$ (7)

Figure 2. Architecture of the Long Short-Term Memory



Source: Authors

Figure 3. Modified BLSTM network structure



Source: Authors

The BLSTM unit aids in the restoration of ancient texts using modern control mechanisms, which include gates and the concept of long-term memory. This enhances the quality and increases the accuracy of the restoration.

3.2 ATTENTION MECHANISM FOR ANCIENT ARABIC MANUSCRIPT RESTORATION

The attention mechanism, initially designed for image recognition, mimics the human visual process by selectively attending to certain image regions and altering attention as needed (Denil, 2012). The technique used to restore ancient Arabic writings highlights important details while ignoring irrelevant ones, improving the restoration process. Attention, used in visual and verbal processing (Denil, 2012), (Chai, 2019), improves performance.

In machine translation, the attention mechanism enhances translation accuracy by selectively emphasising relevant segments of the input language at each stage, rather than treating all input data uniformly. Our enhanced BLSTM network for manuscript restoration incorporates an attention mechanism to enhance precision. By utilising self-attention (Chen, 2019) on the continuous sequence characteristics extracted from the manuscripts, we enhance the model's capacity to accurately recover delicate details.

For the γ feature vectors hα, where α = 1, 2, . . . , γ, generated by the modified BLSTM network, we introduce a score function (·) to assess the significance of each h^{α}:

$$s^{\alpha} = \Phi(W^{s}h^{\alpha} + b^{s}) \quad (8)$$

Here,

W^{s} denotes the weight and b^{s} denotes the bias. Various activation functions can be used as the scoring function (·), such as linear and tanh. We use the softmax algorithm to standardize the results for attention weighting.

$$n^{\alpha} = softmax(s^{\alpha}) = \frac{exp(s^{\alpha})}{\sum_{\alpha=1}^{\gamma} \exp(s^{\alpha})} \quad (9)$$

The result (o) of our adjusted BLSTM is calculated by combining the feature vectors with their attention weights.

$$o = \sum_{\alpha=1}^{\gamma} n^{\alpha} * h^{\alpha} \quad (10)$$

This method orders the elements within the Arabic sources based on their importance to strengthen the restoration process. The information provided by the attention mechanism is applied to improve and adjust the final model. The attention method increases the accuracy and quality of restoration results by allowing more accurate rendering of the essential parts of Arabic manuscripts.

4 RESULTS AND DISCUSSION

To conduct our experiments, we utilized Python programming language and Spyder IDE on a PC equipped with a 64-bit processing system. The computer had an Intel Core i7 CPU operating at 3.0 GHz and was supported by 16 GB of RAM.

4.1 THE DATASETS

Given the scarcity of historical Arabic manuscripts, we created a custom dataset for analysis, comprising 23 folders with 3,745 scanned texts. These manuscripts, digitized at a resolution of 6584x4653, resulted in a dataset size of 25.9 gigabytes. The collection spans various periods, genres, and authors, providing a rich resource for study. Each document was meticulously sorted and tagged for easy retrieval, with high-resolution scans capturing intricate details, offering researchers valuable material for in-depth analysis of ancient Arabic manuscripts.

4.2 DATA AUGMENTATION IN THE PRESERVATION OF ANCIENT ARABIC MANUSCRIPTS

Restoring ancient Arabic texts is difficult due to natural decay and other factors. Overcoming these problems and assisting recuperation require effective data augmentation. Four custom data improvement approaches for the Arabic OCR project expanded the dataset from 3,745 to 55,041 photos. This large increase in document diversity enables full representation of styles and deterioration patterns, improving the restoration algorithm. Researchers, academicians, and conservators protecting cultural artefacts benefit from these modern methods.

4.2.1 Gaussian Noise Augmentation

To mimic the imperfections and impurities found in old historical literature, Gaussian noise is added to each image. This approach prepares the restoration model to handle deteriorated and noisy manuscripts, making it more resilient.

4.2.2 Blurring Augmentation

"Blurring simulates the natural signs of aging and degradation seen in antique books. This technique helps the model correct fading and distorted regions, improving text clarity and characterization.

4.2.3 Sharpness and levels-brightness modification.

Adjusting contrast and brightness levels recreates the lighting and fading effects common in early prints. This technique enhances readability and visual appeal while preserving each manuscript's unique characteristics.

4.2.4 Cutout Augmentation

Cutout augmentation involves randomly masking portions of the manuscript with rectangles, simulating damage or missing sections. This technique challenges the model to restore coherence and cohesion among sentences, even in heavily damaged texts. By combining Gaussian noise, blurring, contrast adjustments, and cutout augmentation, we developed a robust restoration model that effectively addresses the various degradation modes common in old Arabic manuscripts. This comprehensive approach ensures precise text repair and preservation of these valuable historical documents. Table 1 provides the detailed parameters for each of these techniques.

Table1. Data Augmentation Parameters

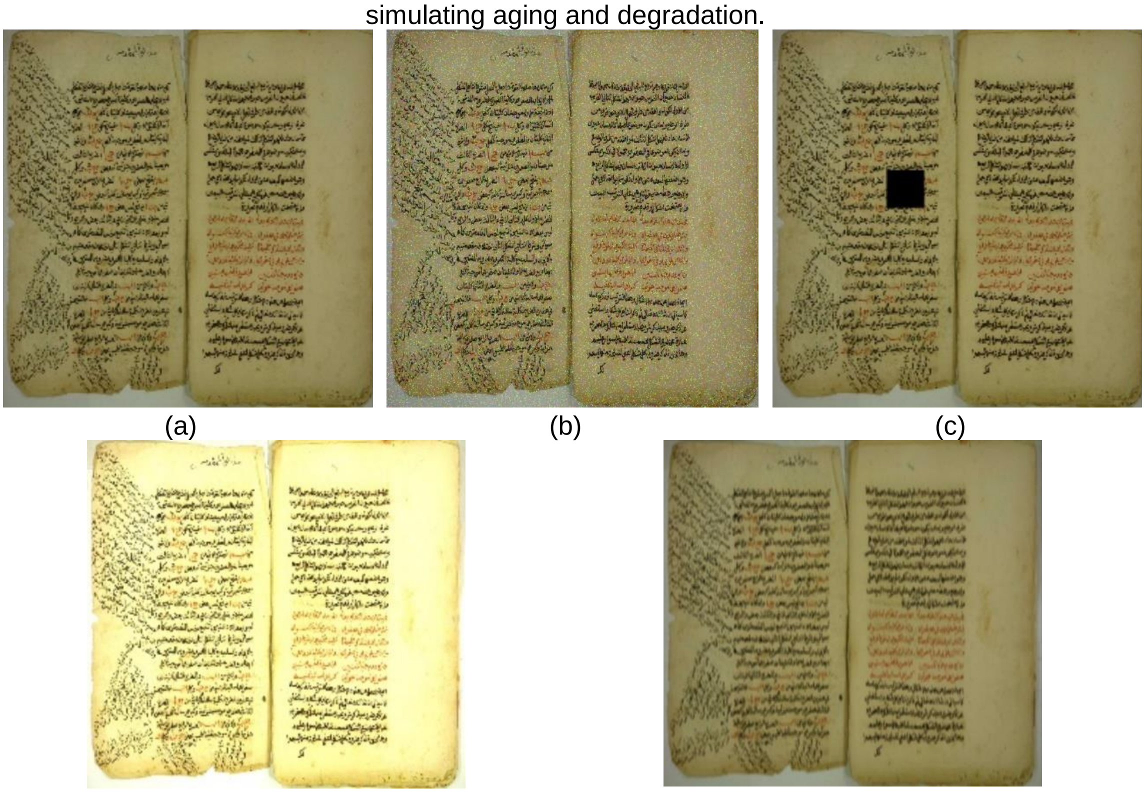
	Gaussian Noise	Blurring	Contrast and Brightness	Cutout
Technique 1	0.0015	0.0035	1.0	20x20
Technique 2	0.0020	0.0040	1.2	25x25
Technique 3	0.0025	0.0045	1.4	30x30
Technique 4	0.0030	0.0050	1.6	35x35
Technique 5	0.0035	0.0055	1.8	40x40

Source: Authors

Table 1 outlines the precise parameters employed for each data augmentation technique, tailored to address deterioration in old Arabic manuscripts. Key settings include Gaussian noise levels, blurring intensity, contrast and brightness adjustments, and Cutout mask size. These parameters were meticulously optimized to enhance restoration outcomes, ensuring the effective handling of common degradation patterns and improving the overall quality and readability of the manuscripts.

Figure 4 visually demonstrates the four data augmentation strategies employed in this study to restore ancient Arabic texts.

Figure 4. Stages of image data augmentation for restoring ancient Arabic manuscripts: (a) Original image, baseline for comparison, (b) Noisy image with Gaussian noise, (c) Cutout image with random rectangular masks, (d) Contrast and Brightness adjusted image, (e) Filtered image simulating aging and degradation.



(a) (b) (c)

(d) (e)

Source: Authors

These robust image data augmentations collectively enhance the model's ability to handle various degradation patterns observed in ancient Arabic manuscripts. This results in improved accuracy in the restoration process, contributing significantly to the preservation of these priceless historical artifacts.

4.3 EXPERIMENTAL STEPS

We employed the Modified Attention-Based Bi-Directional Long Short-Term Memory (M-AB-LSTM) neural network for Arabic handwriting identification. The methodology encompassed several critical steps. Initially, images were resized to [800x566] pixels and their pixel values standardized to a [0-255] range to ensure consistency with the model's input requirements. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets.

During the training phase, hyperparameters—including learning rate, batch size, training epochs, and optimizer—were carefully selected to optimize model performance. Specifically, we utilized 80 training epochs, a batch size of 64, a learning rate of 0.001, AdamW as the optimizer, Contrastive Loss as the loss function, and a regularization value of 0.0010. These configurations were pivotal in refining the model for enhanced accuracy.

The model was trained on the training subset, with continuous evaluation on the validation subset to adjust parameters and mitigate overfitting. The model's efficacy was rigorously assessed on the test set to ensure accuracy and reliability in Arabic handwriting detection. This comprehensive approach enabled effective training and validation of the M-AB-LSTM model for this specific task.

4.4 ANALYSIS AND EVALUATION OF BLSTM AND M-AB-LSTM'S PERFORMANCE IN THE RESTORATION OF OLD ARABIC MANUSCRIPTS

To accurately evaluate the effectiveness of our restoration processes, we employed several objective criteria:

PSNR (Peak Signal-to-Noise Ratio): This metric measure the quality of a reconstructed image compared to the original. It assesses the ratio of the peak signal power (the highest possible value for a pixel) to the noise power within the image. A higher PSNR value indicates a greater similarity between the original and the reconstructed images. PSNR is calculated using the mean squared error (MSE) between the original and reconstructed images:

$$PSNR = 10log_{10}(\frac{Max^2}{MSE}) \quad (11)$$

Where

Max is the highest pixel value in the image (e.g., 255 for an 8-bit image).

SSIM (Structural Similarity Index Measure): SSIM measures the structural similarity between two images by considering brightness, contrast, and structural details. It produces a value between -1 and 1, where 1 indicates perfect similarity. SSIM is constructed using three components: brightness (l), contrast (c), and structure (s):

$$SSIM = (l \times c \times s)^{\left(\frac{1}{3}\right)} \quad (12)$$

Sharpness: Sharpness refers to the clarity and precision of an image, characterized by intricate details and well-defined edges. Sharpness can be quantified using methods such as gradient magnitude or the variance of the Laplacian operator. The variance of the Laplacian is calculated by applying the Laplacian operator to the image and then determining the variance of the resulting values:

$$L = \Delta^2(I) = \nabla^2(I) \quad (13)$$

Where

L isVariance of the Laplacian, Δ^2 is the Laplacian operator, and I is the image. Higher Laplacian variance values indicate greater sharpness due to sharper changes and finer details in the image.

AMBE (Absolute Mean Brightness Error): AMBE measures the difference in brightness between the original and reconstructed images. It is computed as the absolute difference between the mean brightness values of the two images:

$$AMBE = |mean(original) - mean(reconstructed)| \quad (14)$$

Table 2 presents the results from evaluating the BLSTM and M-AB-LSTM models, as well as the condition before restoration. These results highlight the performance of these models in restoring ancient Arabic manuscripts.

Table 2. The results obtained from the evaluation of BLSTM and M-AB-LSTM

Model	PSNR	SSIM	Sharpeness	AMBE
Before Restoration	23.20	0.79	0.70	0.35
BLSTM	30.50	0.95	0.90	0.24
M-AB-LSTM	33.70	0.97	0.96	0.12

Source: Authors

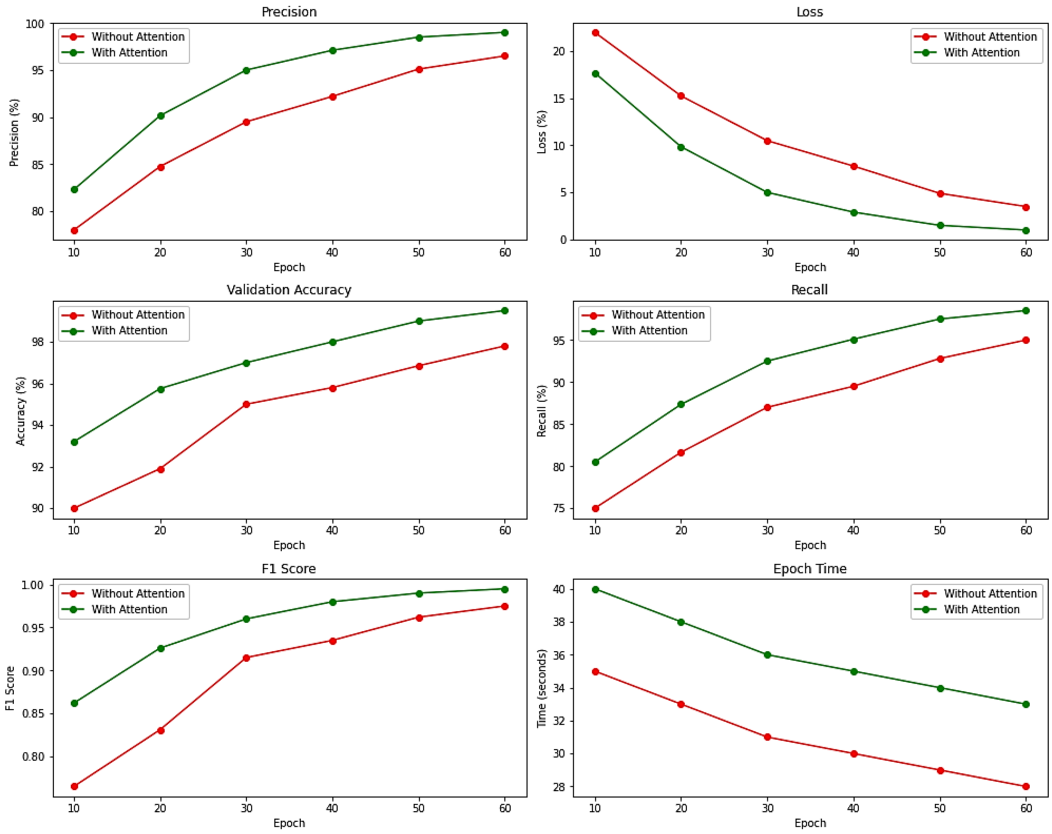
With a PSNR of 23.20, SSIM of 0.79, sharpness at 0.70, and an AMBE of 0.35, the image quality was significantly subpar prior to restoration, suggesting significant structural and brightness issues. The deployment of the BLSTM model resulted in significant improvements, including a PSNR of 30.50, SSIM of 0.95, sharpness of 0.90, and an AMBE of 0.24.

These metrics indicate improved image quality, structural similarity, and brightness accuracy. Conversely, the M-AB-LSTM model demonstrated superior restoration across all metrics, with a PSNR of 33.70, SSIM of 0.97, sharpness of 0.96, and an AMBE of 0.12. The efficacy of both the BLSTM and M-AB-LSTM models in the restoration of ancient Arabic manuscripts is emphasised by these findings.

4.5 IMPACT OF ATTENTION MECHANISM ON BLSTM MODEL PERFORMANCE

The effect of the Attention Mechanism on the model's performance is clearly demonstrated in Figure 5. This figure highlights the results of the BLSTM model without the Attention Mechanism, focusing on the testing outcomes to provide a clear comparison with the training results.

Figure 5. Performance Comparison of BLSTM with and without the Attention Mechanism across Various Metrics



Source: Authors

The comparison between the BLSTM model with and without the Attention Mechanism reveals significant improvements across various metrics when the Attention Mechanism is applied:

- **Precision**: The model with attention starts at 82.30% and reaches 99.00%, compared to 78.00% to 96.50% without attention. This clearly shows that the Attention Mechanism greatly enhances the model's accuracy.
- **Loss**: With attention, the loss decreases sharply from 17.70% to 1.00%. Without attention, it drops from 22.00% to 3.50%. This indicates that the model converges faster and more effectively with the Attention Mechanism.
- **Validation Accuracy**: The model with attention improves from 93.20% to 99.50%, while without attention, it goes from 90.00% to 97.80%. This demonstrates that the Attention Mechanism helps the model generalize better to unseen data.

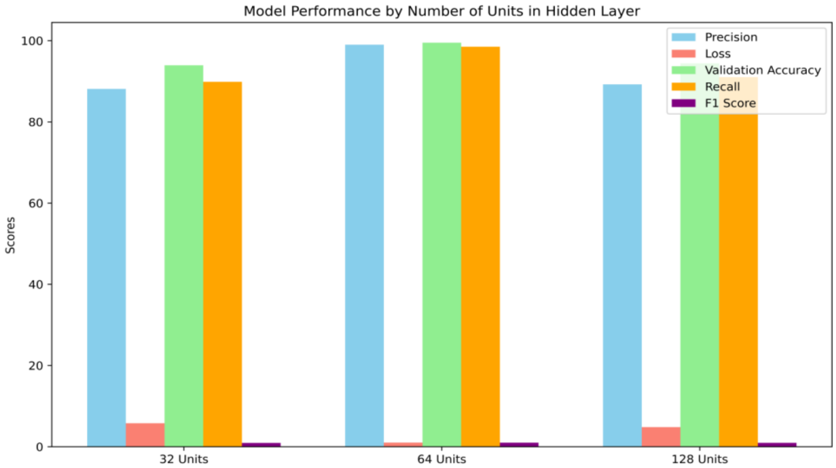
- **Recall**: Recall improves from 80.50% to 98.50% with attention, compared to 75.00% to 95.00% without it. This means the model with attention is better at identifying relevant cases.
- **F1 Score**: The F1 score is higher with attention, improving from 0.862 to 0.995, compared to 0.765 to 0.975 without. This balanced measure of precision and recall confirms the superior performance with the Attention Mechanism.
- **Specificity**: Specificity increases from 85.00% to 98.00% with attention, compared to 80.00% to 95.00% without. This indicates that the model with attention has fewer false positives.

Overall, adding the Attention Mechanism to the BLSTM model significantly boosts its performance, making it more accurate, reliable, and efficient across all these important metrics

4.6 THE IMPACT OF VARYING HIDDEN LAYER UNITS

Choosing the right number of units in the hidden layers is essential for maximizing the performance of BLSTM models when re-writing old Arabic texts. This choice significantly affects the model's ability to detect and represent detailed insights from raw data. The performance of the model in Figure 6 is below as noted through varying the number of units in the hidden layers.

Figure 6. Impact of Hidden Layer Units on BLSTM Model Performance for Restoring Old Arabic Texts



Source: Authors

As illustrated in Figure 6, the model with 64 units in the hidden layer outperforms the others, achieving the highest scores across all metrics: precision, loss, validation accuracy, recall, and F1 score. This clearly indicates that a hidden layer size of 64 units is the most effective for this task.

4.7 THE INFLUENCE OF DIFFERENT LOSS FUNCTION TYPES

Choosing the right loss function is crucial for restoring Arabic manuscripts with damaged content. This choice directly affects the model's ability to recreate fine visual details, which is essential for preserving the historical and cultural significance of these works. Table 3 shows the performance of our BLSTM model using different loss functions, underscoring the importance of this decision in the restoration process.

Table 3. The Influence of Different Loss Function Types on Model Performance

Model Configuration	Precision	Loss	Validation Accuracy	Recall	F1 Score
M-AB-LSTM (MSE Loss)	94.22%	5.70%	95.29%	93.08%	0.932
M-AB-LSTM (Contrastive Loss)	99.00%	1.00%	99.50%	98.50%	0.995
M-AB-LSTM (Perceptual Loss)	98.24%	3.15%	97.02%	97.10%	0.954

Source: Authors

The results in Table 3 clearly demonstrate the critical importance of selecting the appropriate loss function for restoring degraded Arabic manuscripts. Among the tested options, Contrastive Loss emerged as the most effective, achieving the highest scores across all metrics: precision, loss, validation accuracy, recall, and F1 score. This makes it the optimal choice for this restoration task. Utilizing Contrastive Loss is vital not only for preserving the historical and cultural significance of these manuscripts but also for maintaining their visual integrity and for aligning the restoration process with human perception standards.

5 COMPARING OUR APPROACH WITH STATE-OF-THE-ART METHODS

Table 4 provides an in-depth analysis of our proposed technique, allowing us to compare it with methods used in previous studies. It highlights the differences in outcomes between traditional neural networks and our innovative approach, which uses deep learning to boost efficiency and effectiveness.

Table 4. Comparative Evaluation of Proposed Approach and State-of-the-Art Methods

Methods	Year	Deep Learning Features	Dataset	Results
(Loh, 2022)	2015	Multi-headed Recurrent Neural Network (RNN)	PAN 2014	Higher than 80% AUC
(Potthast, 2017)	2017	Confusion between deep learning and (TFIDF) model	Four tweet collections from Twitter	64% Arabic authors identification accuracy
(Boukhaled, 2022)	2018	Four deep learning models: sentence-level GRU, article-level GRU, article-level LSTM, and article-level Siamese network	(Reuters, 5000) (Gutenberg,1286)	Article-level GRU recorded 69.1% and 89.2% accuracy on Reuters and Gutenberg datasets respectively
(He, 2019)	2018	Three methods: 1) Baseline, 2) linear adaptive, and 3) deep adaptive learning	(CVL, 99513)(IAM, 49625)	Deep adaptive learning achieved 78.6% and 69.5% top-1 recognition rates, as well as, 93.7% and 86.1% top-5 recognition rates using the CVL and IAM datasets respectively
(Khayyat, 2020)	2020	Transfer learning from MobileNetV1-100-244	Collected ancient Arabicmanuscripts (8638)	95.59% accuracy
		Transfer learning from ResNetV2-50		96.23% accuracy
		Transfer learning from DenseNet201		95.83% accuracy
		Transfer learning from VGG19		95.91% accuracy
Proposed method	2024	Modified Attention-Based Bidirectional Long Short-Term Memory (M-AB-LSTM)	Collected ancient Arabicmanuscripts (3745)	99.50% accuracy

Source: Authors

Table 4 presents a comprehensive evaluation of the restoration and preservation of Arabic manuscripts, demonstrating the better effectiveness of our suggested strategy compared to conventional methods. The utilisation of the M-AB-LSTM model in our approach results in a validation accuracy of 99.50%, showcasing its precision and effectiveness in the restoration of culturally relevant texts. This cutting-edge technique improves the precision and ease of understanding of ancient documents, providing advantages to scholars and academics. Our revolutionary preservation strategy for Arabic manuscripts relies heavily on deep-learning algorithms and sophisticated image restoration techniques, which play a crucial role in achieving high accuracy.

6 CONCLUSION

This Advanced deep learning and image improvement technologies have been used to improve and preserve antique Arabic literature in this research. The restoration model is more efficient since our solutions combat the deteriorating tendencies that influence most cultural objects.

General experimentation had numerous phases. Phase I preprocessed data, whereas Phase II validated models. PSNR, SSIM, sharpness, and AMBE were used to evaluate this paper's M-AB-LSTM model. The Yiqian Press condition scores and the BLSTM model showed that our model is practical for preserving historical manuscripts after restoration.

We also examined hidden units and loss functions, confirming that Perceptual Loss improves results. This has led to new research paradigms in this sector.

Comparisons with prior studies demonstrate that this method is the best for reconstructing ancient Arabic texts, with an accuracy percentage of 99.50%. Innovations improve the accuracy of protecting historical assets, emphasizing the need to continue preserving their cultural and historical worth.

Future research should generate scholars who can offer data in a multi-dimensional integrated format with semantic analysis and multidisciplinary collaboration. SV must also be improved and advanced methods for massive data and complex text restoration found. Examining adequate scientific studies and successful restoration cases will improve restoration efficacy.

These innovations will be used to secure and preserve civilizations’ cultural records in manuscripts in the coming years and decades. This will let future generations learn and follow their ancestors' practices.

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