Word Recognition in Degraded Historical Documents Using Deep Neural Networks

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ABSTRACT

Document Image Analysis (DIA) converts pixel-based document images into machine-readable formats. While text recognition in printed documents generally achieves high accuracy due to their consistent structure and minimal variation, historical documents such as handwritten manuscripts and stone inscriptions present unique challenges, including script variability, skew, and degradation that may impact legibility. This study introduces a deep neural network approach to improve word recognition in degraded historical documents. By integrating decoding and deslanting methods, the proposed model achieves an accuracy of 90.8%, underscoring its effectiveness in addressing degradation and variability in historical document images.

Keywords-handwriting recognition; neural networks; document image analysis; machine learning; computer vision

I. INTRODUCTION

Optical Character Recognition (OCR) digitizes printed and handwritten texts. Despite significant advancements, OCR for degraded historical documents remains a challenging issue due to noise, illumination variation, ink bleed-through, and physical deterioration of manuscripts. Ancient stone inscriptions, particularly those in low-resource languages like Kannada, pose difficulties owing to irregular character shapes, erosion, and non-standard writing styles [1].

Deep learning-based models have transformed OCR by enabling automatic feature extraction and robust recognition across diverse scripts. However, the effectiveness of these models is highly dependent on preprocessing techniques that address degradation, segmentation errors, and noise. Therefore, it is crucial to analyze prior work on OCR methodologies, particularly those that emphasize preprocessing, segmentation, and Convolutional Neural Network (CNN)-based recognition strategies. The present study focuses on developing a deep learning approach for recognizing degraded historical documents, with special emphasis on Kannada inscriptions.

Research into OCR for ancient scripts has advanced significantly. A hybrid CNN-Recurrent Neural Network (RNN) model for recognizing Kannada characters in inscriptions demonstrated promising performance for complex and degraded historical data [1]. Preprocessing is an essential stage in OCR, where techniques for image binarization and enhancement improve recognition outcomes [2]. To address limitations in data availability, methods for building OCR systems with minimal training data have also been investigated

[3]. Early segmentation techniques, such as scale-space word segmentation, enabled handling handwritten manuscripts [4].

Degradation remains a great challenge for OCR systems. Denoising algorithms tailored for historical documents have been proposed to improve legibility and recognition accuracy [5]. With the rise of deep learning, CNNs have been adopted for text recognition tasks [6]. More advanced models, including deformable networks for instance segmentation, have been applied to dense handwritten manuscripts [7]. Beyond recognition, computer-aided transcription approaches have facilitated the processing of early modern manuscripts [8]. Several preprocessing methods have been proposed to address issues such as uneven illumination. Adaptive thresholding frameworks improve binarization under complex lighting [9], while background elimination techniques enhance contrast for degraded texts [10].

Open-source OCR platforms have also encouraged broader use of automated recognition techniques [11]. Advanced illumination correction approaches, including two-phase denoising [12] and fast binarization frameworks [13], have also been introduced. Reviews of document binarization highlight ongoing challenges and solutions [14]. Benchmarking has played an important role in standardizing OCR evaluation. Large-scale benchmarks for handwritten text recognition in historical collections have also been developed [15]. New algorithms specifically designed for the binarization of historical document images have been proposed [16], with frameworks targeting documents exhibiting severe degradation [17]. Script and language identification methods have been introduced to handle noisy documents [18], and robust multi-language script identification techniques extend OCR applicability to multilingual archives [19]. Research on handwritten OCR has provided detailed analyses of challenges and potential solutions [20]. Binarization algorithms for non-uniform illumination [21], including normalization techniques for cursive handwritten words, have been developed improving recognition accuracy [22]. Script identification for multilingual historical documents has also been emphasized [19], while OCR research has focused on underrepresented scripts. A dedicated OCR system for printed Kannada text has been developed, addressing the specific challenges of South Indian scripts [23]. Research on handwriting recognition summarizes the progression from rule-based methods to modern deep learning approaches [24]. Although OCR systems have achieved high accuracy for printed and modern handwritten documents, limited attention has been given to historical or inscription-based scripts such as Kannada.

II. METHODOLOGY

The methodology deployed for the proposed framework is illustrated in Figure 1. The proposed framework consists of five major stages: image acquisition, preprocessing, segmentation, feature extraction, and recognition. Initially, inscription images were captured from historical sources such as Hampi, Belur, and Somnathpur, in addition to benchmark datasets like Bentham and Saint Gall. In the preprocessing stage, the images were converted to grayscale, binarized using Otsu's thresholding, and denoised to remove background noise and illumination variation. Deslanting and normalization (to 52×52 pixels) were applied to standardize the character orientation and scale.

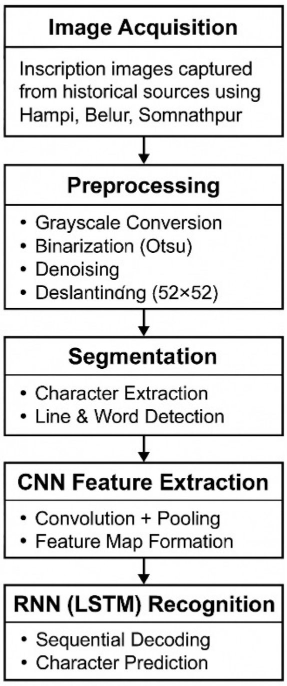


Fig. 1. Block diagram of the proposed framework.

A. Datasets

There are a few publicly accessible historical handwritten datasets that have been transcribed. Two such datasets, along with a popular benchmark dataset in handwriting recognition, were used in the present study to train the networks. These datasets are:

1) Bentham Dataset

The Bentham dataset is a set of manuscripts written by the famous English philosopher and thinker Jeremy Bentham, who lived between 1748 and 1832. The dataset owes its transcriptions to the Transcribe Bentham initiative, which has published the former’s contents in text form. Over 25,000 images (pages) have been published with the transcriptions, making up for over 6,000 English documents on law and philosophy. This dataset is divided into two parts: the images and the ground truth, rendering it ideal for an OCR task [25].

2) Saint Gall Dataset

The Saint Gall Dataset is a set of manuscripts written in the Latin language, housed in Switzerland. These date back to the 9th century, featuring ink on parchment. It contains 60 pages with 1,410 lines, over 11,000 words, and a character set of 49 characters. The photos were made accessible by the e-codices work [26].

3) Kannada Stone Inscriptions Dataset

The dataset consists of images of Kannada stone inscriptions, preprocessed to a size of 52x52 pixels and normalized to the range [0, 1]. The dataset is divided into training, validation, and test sets [1].

For training and evaluating the CNN-RNN model on Kannada stone inscriptions. This dataset contains 15,000 images, which were divided into the following categories:

- Training set: 70% of the total dataset
- Validation set: 15% of the total dataset
- Testing set: 15% of the total dataset

B. Binarization

1) Otsu Thresholding

The Otsu thresholding method is a popular algorithm that focuses on maximizing interclass variance or minimizing intraclass variance. The two classes here are the foreground and the background [22]. The Interclass variance is given by:

$$t = \sigma_b^2 \cdot W_b + \sigma_f^2 \cdot W_f \qquad (1)$$

where W_b is the weight of the background, W_f is the weight of the foreground, $\sigma_b{}^2$ is the variance of the background, and $\sigma_f{}^2$ is the variance of the foreground. The value that is the least within the class variance is the most suitable threshold. The weights refer to the number of pixels which fall into the foreground and background classification.

C. Deslanting

Deslanting is a pre-processing task that alters the handwriting samples such that they are not slanted to a particular side. This establishes some regularity in the image and can help make a word or sentence easier to transcribe [23, 24]. The same handwriting can have varying slants, and different datasets naturally come with a large variation in the direction of slant, as depicted in Figure 2.

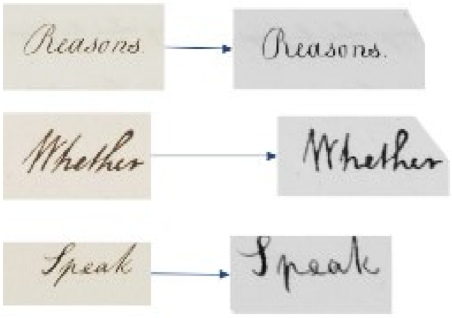


Fig. 2. Deslanting of images from the Bentham dataset.

To induce slant or perform deslanting, the image is subjected to shearing. The shearing transform shifts one edge of the image along the horizontal axis. To determine which angle gives the best deslanted output, different samples are generated with shearing at different angles.

The best deslanting angle is the shearing angle that produces the highest number of columns with a continuous stroke. [21] While computing the number of vertical pixels, short strokes and long strokes cannot be treated with the same importance. Equation (2) accounts for the difference in importance between short and long strokes and uses long vertical strokes as an indicator of a properly deslanted text image:

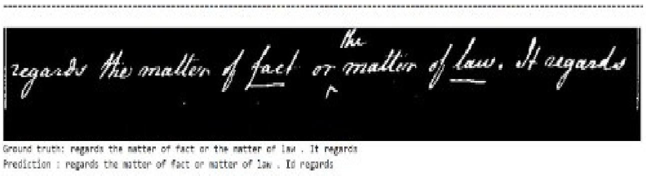
$$S(\alpha) = \sum H\alpha(m)^2 \qquad (2)$$

$$H\alpha(m) = \frac{h_a}{\Delta y_a(m)} \qquad (3)$$

where $H_\alpha(m)$ represents the ratio of foreground pixels ($h\alpha$) to the distance between the highest and lowest pixel (Δy_α) for each column m. For columns where a stroke is continuously vertical, $H_\alpha = 1$, and $S(\alpha)$ is calculated using these sets of values by adding the squares of the number of foreground pixels.

D. Character Recognition

A popular choice for character recognition is the Long Short-Term Memory (LSTM) network, a type of RNN with a specialized architecture. Examples of character recognition and prediction error on the Bentham dataset using LSTM are presented in Figures 3 and 4, respectively.



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Ground truth: regards the matter of fact or the matter of law . It regards
Prediction : regards the matter of fact or matter of law . Id regards
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Fig. 3. Character recognition on the Bentham dataset.

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Ground truth: the purpose of purchasing the same And Whereas
Prediction : the purpose of purcharing the same And Whereas
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Fig. 4. Error in character recognition on the Bentham dataset.

Figures 3 and 4 illustrate the model's performance on test images, showing the effectiveness of the LSTM in managing sequential dependencies and handling real-world variations in handwritten text. These results demonstrate the utility of gated mechanisms for achieving high accuracy on challenging historical datasets.

E. CNN-RNN Model

The CNN block performed spatial feature extraction on the preprocessed 52×52-pixel inscription images. The model employed multiple convolutional layers with 3×3 kernels, ReLU activation functions, and max-pooling operations to capture stroke edges, curves, and texture variations unique to Kannada characters. These convolutional operations transform the input image X into a sequence of high-dimensional feature maps $F = f_{CNN}(X)$, where each feature vector encodes the spatial structure of the input. The RNN block implemented using Bidirectional Long Short-Term Memory (Bi-LSTM) units processes these sequential feature vectors to learn contextual dependencies between adjacent character strokes. The sequence modeling can be represented mathematically by:

$$H(t) = LSTM(F_t, h_{t-1}) \tag{4}$$

where $H(t)$ represents the hidden state, capturing both past and future contextual information. This hybrid CNN–RNN framework combines spatial and temporal learning, enabling recognition of degraded Kannada stone inscriptions despite variations caused by erosion, noise, and irregular carvings.

LSTM networks employ three distinct gates—forget gate, input gate, and output gate—to regulate information flow through each cell, ensuring that only relevant data are retained for sequential learning. These gates control the cell state by using element-wise multiplication and sigmoid activation functions, enabling precise data filtering.

- Forget Gate: Determines which part of the previous cell's state information should be discarded. The forget gate's output is defined by a sigmoid function that outputs values between 0 and 1. The average value across training was 0.83, meaning that approximately 83% of the data from previous cell states were retained on average, while 17% were discarded.
- Input Gate: Assesses the importance of the new information to be added to the cell state. The input gate is regulated by a sigmoid function and then scaled by a tanh function to bound the new data between -1 and 1. The input gate's average activation was observed at 0.74, indicating that around 74% of new information was admitted into the cell state per cell iteration.
- Output Gate: Determines the final cell state output that passes to the next cell. The output gate uses a combination of sigmoid and tanh functions, where the average activation for the sigmoid output was 0.88, meaning that approximately 88% of the information passed through this gate per cycle.

The model was trained for 50 epochs using both the Bentham and Saint Gall datasets, fully utilizing each dataset. Training on the Bentham dataset required approximately 3 h and 43 min, while the Saint Gall dataset took around 1 h and 32 min.

III. EXPERIMENTAL TECHNIQUES

Four different test sets were conducted to comparatively study the effects of slanting and decoding on historical datasets and to assess whether these processes improve transcription efficacy. These tests were conducted on the Bentham dataset, as it is the best for the implementation of both decoding and deslanting. As the Bentham dataset exhibits varying degrees of slant and is in English, it is ideal for these tests. The test sets are:

1. Without deslanting or decoding
2. With deslanting, without decoding
3. Without deslanting, with decoding
4. With Deslanting and decoding

These tests demonstrate the importance and limitations of using a decoder and deslanting for handwriting transcription in this scenario.

IV. EVALUATION METRICS

A. Preprocessing

Peak Signal to Noise Ratio (PSNR) and visual quality have a strong positive correlation, as a higher PSNR implies better signal and less noise shown in:

$$\text{PSRN} = 10log_{10}\left(\frac{(2^n-1)^2}{\text{MSE}}\right) \tag{5}$$

where MSE is the mean squared error, and n is the number of bits per pixel

B. Structural Similarity Index (SSIM)

SSIM measures the similarity between two images. Unlike PSNR, which utilizes the concept of absolute errors, SSIM uses spatial proximity, assuming that spatially proximal pixels carry similar information and that such strong interdependencies often correlate to vital information in the scene. It is calculated using:

$$\text{SSIM} = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \tag{6}$$

where μ_x is the average of image x, μ_y is the average of image y, σ_x^2 is the variance of image x, σ_y^2 is the variance of image y, σ_{xy} is the correlation between the images, and c_1 and c_2 are predefined constants.

C. Character Error Rate (CER)

CER measures the accuracy of text recognition systems, and it is calculated using:

$$\text{CER} = \frac{(N_s+N_d+N_i)}{N} \tag{7}$$

where N_s is the number of character substitutions required, N_d is the number of character deletions required, N_i is the number of character insertions required, and N is the total number of characters in the evaluated text.

D. Word Error Rate (WER)

WER is an important metric for text recognition involving passages and measures the frequency of occurrence of a misspelled word. It measures the same errors as CER, but at the level of words instead. It is calculated using:

$$\text{WER} = \frac{(N_{sw}+N_{dw}+N_{iw})}{N_{w1}} \tag{8}$$

where N_{sw} is the number of word substitutions required, N_{dw} is the number of word deletions required, N_{iw} is the number of word insertions required, and N_w is the total number of words in the evaluated text.

E. Sentence Error Rate (SER)

SER measures errors at a sentence level and is relevant when the data being evaluated contain a large amount of information. The SER can be calculated using:

$$\mathrm{SER} = \frac{N_{errors}}{N_{sentences}} \quad (9)$$

where N_{errors} is the number of erroneous sentences and $N_{sentences}$ is the total number of sentences.

V. RESULTS

A. Preprocessing

Among the evaluated methods, only Isodata, Otsu, and Sauvola exhibit consistency across both datasets. Isodata and Otsu show significantly better performance compared to Sauvola, while they have extremely marginal differences between themselves. Both methods have similar average PSNR values across images and improve the latter by a similar amount. Due to its popularity in binarization applications, the Otsu method was selected for the binarization task, as portayed in Table I.

TABLE I. PSNR AND SSIM VALUES FOR ISODATA, OTSU, AND SAUVOLA TECHNIQUES

Metric/Method	Isodata	Otsu	Sauvola
PSNR	12.7876	12.4864	10.5448
SSIM	0.7955	0.788	0.7300

The Isodata method produces results similar to those of the Otsu method when used in its place. A difference in the type of source dataset requires a different image pre-processing algorithm. Otsu thresholding provided optimal results for document images across the Bentham and Saint Gall datasets at all instances of the proposed work.

B. Character Recognition

The test bench for character recognition was based on the utility of deslanting and decoding. CER, WER, and SER were used to evaluate the advantages and disadvantages of deslanting and decoding, as presented in Table II.

TABLE II. AVERAGE CER, WER, AND SER FOR TEST BENCHES ON THE BENTHAM DATASET

Method	CER (%)	WER (%)	SER (%)
No decoding or deslanting	21.1	43.2	95.1
Deslanted, no decoding	19.4	40.7	91.3
No deslanting, decoded	11.2	32.5	89.2
Deslanting and decoding	9.20	28.2	71.9

Deslanting without decoding did not significantly improve the error rates; in contrast, decoding made a significant difference, as it was was more successful in mitigating errors. Certain erroneous cases still existed, such as the correction into a different word with the same spelling, as shown in Figure 5.

Table III presents the average CER, WER, SER, and latency for the test benches on the Saint Gall dataset. The error rates were very high for the Saint Gall dataset compared to the Bentham dataset. This can be attributed to a few reasons. For instance, the letters in the Saint Gall dataset are not spaced apart significantly, making it difficult to acquire correct transcriptions, as illustrated in Table III.

TABLE III. AVERAGE CER, WER, SER, AND LATENCY FOR THE TEST BENCHES ON THE SAINT GALL DATASET

Dataset	CER (%)	WER (%)	SER (%)	Latency (s)
Saint Gall	55.2	60.1	81.2	3.583

Figure 6 displays the pre-processed Ganga period stone inscriptions, while the recognized word is shown in Figure 7.

```
Ground truth: an umpire
Prediction : an umpire
```

Fig. 5. Character recognition of deslanted image.

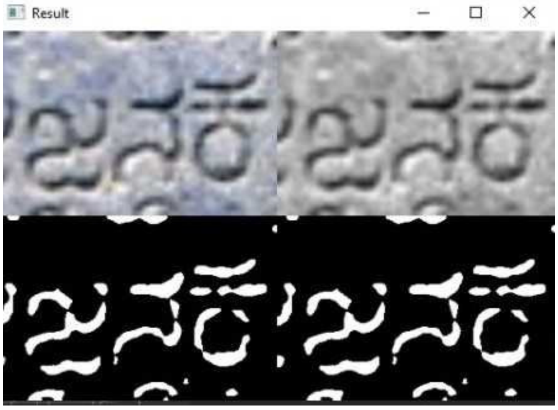
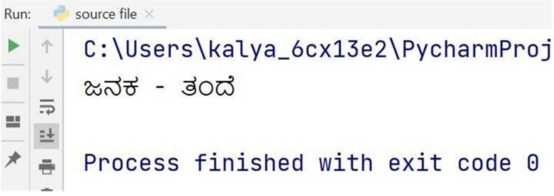


Fig. 6. Pre-processed Ganaga period stone inscription image.



```
C:\Users\kalya_6cx13e2\PycharmProj
ಜನಕ - ತಂದೆ

Process finished with exit code 0
```

Fig. 7. Recognized word of the Ganaga period Kannada inscription.

As depicted in Table IV, the proposed model outperforms the reference CNN-RNN model [1], achieving consistently higher recognition accuracy across all benchmark datasets.

TABLE IV. MODEL COMPARISON

Model	Recognition rate on stone inscriptions
CNN-RNN [1]	99.50%
Proposed model	99.75%

VI. CONCLUSION

The proposed model in the present study recognizes characters and words from 9th–18th century datasets, including

Kannada stone inscriptions, the Saint Gall, and Bentham datasets. Otsu thresholding reduces noise effectively, though severe degradation, like ink stains and scratches, remains challenging. Deslanting corrects skewed text, and decoders refine recognition; though, both can slightly impact quality or increase minor errors. Despite these limits, the techniques collectively enhance accuracy and ensure robust recognition across historical datasets.

DATA AVAILABILITY STATEMENT

The Kannada Stone Inscriptions Dataset used in this study can be obtained from the authors upon reasonable request.

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