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Challenges and Opportunities in Brahmi Script Recognition using Artificial Intelligence

Tushar B. Kute[1], Dr. Premanand P. Ghadekar[2]

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Abstract: This study presents a comprehensive analysis of OCR systems specifically designed for stone inscriptions in various ancient languages. It focuses on the techniques, challenges, and advancements related to digitizing and preserving ancient texts engraved on stone. The unique characteristics of stone inscriptions, including diverse languages, ancient scripts, erosion, weathering, and non-uniform lighting conditions, are discussed. Techniques for image enhancement, feature extraction, and recognition models are investigated, with a specific emphasis on handling complexities like the Brahmi script. The research examines challenges associated with segmentation, character recognition, and the incorporation of linguistic and historical knowledge. Existing OCR frameworks, evaluation metrics, and recent advancements, such as machine learning, deep learning, and advanced imaging technologies, are presented. This study serves as a valuable resource for researchers and professionals involved in deciphering and preserving ancient stone inscriptions. It identifies opportunities for developing innovative artificial intelligence methods to enhance Brahmi script recognition for stone inscriptions, aiming to achieve better performance and improved accuracy. Promising results have not yet been achieved for OCR systems for various ancient scripts, even though several techniques have been developed So, it is possible to incorporate novel algorithmic techniques of artificial intelligence as well as suitable parameters to gain efficiency and accuracy in existing algorithms.

Keywords: *artificial intelligence, Brahmi script, culture, deep learning, heritage, Indian languages, OCR, stone inscriptions*

1. Introduction

The Brahmi script, renowned for its historical importance and extensive use in ancient India, stands as one of the oldest writing systems globally. Stone inscriptions containing Brahmi script provide invaluable insights into the cultural, linguistic, and historical aspects of ancient civilizations. This proposed work focuses on OCR systems specifically tailored for the recognition and analysis of Brahmi script stone inscriptions.

The utilization of OCR technology significantly contributes to the digitization and preservation of stone inscriptions engraved in the Brahmi script, facilitating broader access and scholarly investigation of these ancient texts. However, recognizing as well as deciphering Brahmi script poses unique challenges due to its complex structure, ligatures, and variations across different regions and time periods.

This study aims to conduct a thorough analysis of different OCR systems specifically developed for stone inscriptions written in the Brahmi script. It explores the techniques, challenges, and advancements in image preprocessing, segmentation, character recognition, and linguistic analysis specific to the Brahmi script.

Researchers, archaeologists, linguists, and cultural heritage professionals involved in deciphering and preserving Brahmi script stone inscriptions can benefit from the insights provided in this survey. By examining being OCR fabrics, tools, and recent advancements, this check aims to offer a precious resource for understanding the state- of-the- art OCR systems acclimatized for the unique characteristics and challenges of Brahmi script gravestone eulogies.

In conclusion, this research provides a comprehensive reference for researchers and professionals engaged in the digitization, preservation, and analysis of stone inscriptions written in the Brahmi script, utilizing OCR systems. It sheds light on the advancements, techniques, and challenges specific to recognizing and interpreting the ancient Brahmi script engraved on stone surfaces.

2. Study of Techniques Used

The study by Devi et al focuses on the development of a software system designed to extract Sinhala text from digital images [1]. The goal is to automatically identify and extract the Sinhala characters present in the images.

The researchers employ a connected components labeling algorithm to address the challenge of overlapping character segmentation. This algorithm detects and labels individual connected regions in the image, allowing for the separation of overlapping characters.

Also, a background thinning grounded approach is employed for the segmentation of touching characters. This

[1] Research Scholar, Vishwakarma Institute of Technology, Pune 411037, INDIA
[2] Professor, Vishwakarma Institute of Technology, Pune 411037, INDIA
** Corresponding Author Email: tushar@tusharkute.com*

approach aims to distinguish and separate characters that are connected or touching each other.

The overall accuracy of the system in extracting Sinhala text from images is reported as 76%. The methodology of the study consists of several modules. The methodology begins by exercising image pre-processing ways to ameliorate the quality and clarity of digital images. These ways aim to ameliorate the overall quality of the images, including reducing noise, enhancing discrepancy, and correcting any deformations or vestiges present in the digital representation of the Javanese calligraphies. By applying these pre-processing techniques, the researchers ensure that the subsequent steps of character segmentation and analysis are performed on images that are optimized for accurate and reliable results. This includes operations such as noise removal, contrast adjustment, and image normalization.

The character segmentation module is responsible for identifying and separating individual characters from the image. The connected components labeling algorithm and the background thinning approach are utilized within this module to achieve accurate segmentation.

After the character segmentation process, the next step in the methodology is to employ a character recognition module. This module is responsible for recognizing and classifying the segmented characters from the Javanese manuscripts. Various machine learning or pattern recognition techniques can be utilized within this module to accurately identify the Sinhala characters. Possible Ways comprise neural networks, support vector machines, decision trees, and deep literacy algorithms. The main ideal is to train the recognition module to rightly identify the specific Sinhala characters grounded on their visual patterns and features uprooted from the segmented images.

Finally, a spell correction module may be implemented to improve the accuracy of the extracted text. This module aims to correct any spelling errors or inconsistencies in the recognized characters by comparing them with a reference database or language-specific rules.

In summary, this study presents a software system that utilizes connected components labeling and background thinning techniques to extract Sinhala text from digital images. The system comprises image pre-processing, character segmentation, character recognition, and spell correction modules. The reported accuracy of the system is 76%.[1]

Bandara et al. proposed a computational method in their work with the primary objective of developing a technique for generating Brahmi alphabet fonts in the Early Brahmi script used in ancient Sri Lankan inscriptions. Their research focuses on creating automated processes that can analyze and process data to accurately produce representative fonts of the Brahmi alphabet. By capturing the intricate details of the script, this method contributes to the study and preservation of the ancient Brahmi script. [2] The methodology revolves around the utilization of computational techniques to create accurate and visually appealing fonts for the Early Brahmi script based on the photographic data obtained from ancient inscriptions found in Sri Lanka. The primary objective is to devise a computational approach for generating Brahmi alphabet fonts from the available photographic data.

Gautam et al.'s exploration paper [3] presents the development of a customized OCR system specifically designed for recognizing the Brahmi script. The paper also includes detailed comparisons with two other scripts, Akkhara-Muni and Ariyaka. The study covers languages similar as Pali, Brahmi, Akkhara- Muni, and Ariyaka.

The proposed algorithm, called MOCR, is utilized for the recognition task. The accuracy achieved for the Brahmi, Akkhara-Muni, and Ariyaka scripts is reported as 85.66%, 85.73%, and 88.83% respectively.

The methodology for recognizing scripts begins with obtaining the input image. Preprocessing steps are then applied to enhance the quality and clarity of the image. These steps include cropping, grayscale conversion, binarization, and noise removal.

Local segmentation is performed using the labelling and joining method. This step helps to separate and isolate individual characters from the script, enabling further analysis.

Feature extraction is carried out using a low and upper approach. This technique focuses on extracting relevant features from the characters that contribute to their recognition.

Finally, character classification is performed to assign the recognized characters to their respective scripts. The classification process aids in distinguishing the characters of Brahmi, Akkhara-Muni, and Ariyaka scripts.

The methodology outlined in this exploration paper integrates preprocessing, original segmentation, point birth, and character bracket ways to develop an acclimated OCR system for the recognition of the Brahmi script. The system's accuracy is evaluated and compared with the recognition of Akkhara-Muni and Ariyaka scripts, offering insights into the algorithm's performance across different script types. [3] The language used here is ancient Pali.

In their exploration paper [4], Suganya et al. propose a methodology for recognizing the ancient Tamil script. The methodology uses Shape and Hough transform methods for point detection, and it integrates Group Search Optimization and Firefly algorithm for point selection. For the recognition phase, Neural Network, J48, Naïve Bayes, and KNN algorithms are employed, achieving reported delicacy situations ranging from 91 to 94.

The methodology begins by landing an image of the ancient Tamil script, followed by the operation of a median sludge to remove noise and enhance the image quality. The preprocessed image is then subjected to binarization to convert it into a binary image.

Segmentation is carried out to isolate individual characters from the script. This step allows for the separation of characters for further analysis.

Feature extraction is performed using shape and Hough transform techniques. These techniques extract relevant information related to the shape and curvature of the characters.

Feature selection is accomplished using Graph Search Optimization and Firefly algorithms. These algorithms aid in selecting the most informative and discriminative features for recognition.

Finally, classification is performed using Neural Network, J48 (C4.5 decision tree), Naïve Bayes, and KNN algorithms. These algorithms utilize the extracted features to classify the characters into their respective categories.

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Suganya et al.'s exploration paper [5] focuses on recognizing the ancient Tamil script using Shape and Hough transform methods for point detection. Their methodology integrates Group Search Optimization and Firefly algorithm for point selection. For the recognition phase, they employed Neural Network, J48, Naïve Bayes, and KNN algorithms, achieving reported accuracy levels ranging from 91 to 94.

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In the paper by Jyothi et al [6], the problem at hand is to develop a higher accuracy model and a faster computational method for recognizing handwritten characters in English, specifically written on palm leaf. The chosen algorithm for this task is Convolutional Neural Network (CNN), known for its effectiveness in image recognition tasks.[6]

The methodology consists of several stages. It begins with data acquisition, where the palm leaf images containing handwritten English characters are collected .Next step involves applying pre-processing techniques to improve the quality of the images, ensuring better recognition results. The pre-processing stage may involve operations such as noise reduction, normalization, and contrast adjustment.

Segmentation is then performed to separate individual characters from the palm leaf images. This step is crucial for accurate recognition and involves techniques to isolate and extract characters from the image background.[6]

A Convolutional Neural Network (CNN) model, utilizing a substantial dataset of labeled palm flake images, is utilized for the recognition task. This process enables the model to effectively grasp the patterns and distinguishing traits of handwritten English characters. Consequently, the trained CNN model exhibits high accuracy in classifying and recognizing characters within new palm leaf images.

The accuracy achieved by this approach is not specified in the provided information. However, CNN models have shown high accuracy in various image recognition tasks, making them a suitable choice for handwritten character recognition.

Overall, the methodology focuses on acquiring data, pre-processing the images, segmenting the characters, and utilizing a CNN model for accurate and efficient recognition of handwritten English characters on palm leaf surfaces.[6]

Subsequently, wavelet transforms are applied for feature extraction. The aim is to extract pertinent features from the script images, thereby facilitating character recognition. These extracted features play a crucial role in the character recognition process.

A Feed Forward Classification approach is implemented for character classification and recognition, leveraging the extracted features. The reported accuracy of this methodology stands at 71%.

The primary objective of the analysis is to assess and compare the efficacy of different wavelet transforms in recognizing the Ancient Grantha Script, particularly in the context of the Sanskrit language. The study aims to evaluate how well each wavelet transform performs in accurately identifying and deciphering the characters within the script. The methodology includes pre-processing, feature extraction using wavelet transforms, and classification using a Feed Forward approach to achieve character recognition.[6]

Gautam et al. [7] present a research paper that introduces a method for recognizing Brahmi characters, both handwritten and printed. The proposed approach for Brahmi script recognition involves four stages: preprocessing the image, segmenting the image into characters, extracting features from the characters, and classifying the characters.

The initial step in the methodology involves taking an input image of Brahmi characters. Following that, preprocessing techniques are employed to remove noise and artifacts from the image, which could affect the recognition process.

Next, the image is segmented to separate individual characters from the input image. This step is crucial for further analysis and feature extraction. Feature extraction techniques are employed to capture relevant information from the segmented characters. In this research, geometric features are utilized to represent the characteristics of the Brahmi characters.

After extracting the features, a classification algorithm, such as Optical Character Recognition (OCR), is utilized to categorize the characters into their respective classes. The algorithm undergoes training on a dataset comprising labeled examples of Brahmi characters.

The method's accuracy is assessed for both handwritten and printed Brahmi characters, and the findings are reported accordingly. For handwritten vowels and consonants, the accuracy is reported to be 91.69% and 89.55% respectively. For printed vowels and consonants, the accuracy is reported as 93.30% and 94.90% respectively.

In conclusion, the research paper presents a methodology for recognizing handwritten and printed Brahmi characters. The proposed method comprises four stages: preprocessing, segmentation, feature extraction, and character classification. The reported accuracy demonstrates the effectiveness of the approach in accurately recognizing Brahmi script characters.[7]

In the paper proposed by Menon et al [8] the problem being addressed is Handwritten Text Recognition (HTR), specifically focusing on handwritten text. The algorithm employed to tackle this challenge is Derivational Entropy. The proposed methodology for this project involves a segmentation-free approach to HTR, where the focus is on recognizing the handwritten text without explicitly segmenting individual characters or words. The derivational entropy doesn’t possess remarkable accuracy. It is needed to employ the machine learning methods here.

The primary goal is to minimize the time and effort involved in creating extensive, high-resolution document datasets [9]. To address this challenge, the proposed solution combines readily available hardware and user-friendly software tools, empowering researchers to efficiently achieve their goal.

The methodology involves several components. Firstly, a hardware design is developed, utilizing equipment such as a DSLR camera, which offers high-resolution image capture capabilities.

Next, software tools are employed to streamline the data collection process. These tools may include features to process the captured images, such as cropping, rotating, adjusting resolution, and performing binarization to enhance document clarity.

By utilizing this low-cost solution, researchers can generate large, high-resolution document datasets more efficiently and with reduced effort and costs. The combination of conventional hardware and simple software tools enables an effective workflow for data collection and processing in an optimized manner.[9]

According to the analysis conducted by Daggumati et al., It has been observed that the symbols in question exhibit a stronger similarity when compared to the Brahmi script.10] The languages involved in the analysis are Phoenician, Brahmi, and the ancient Indus Valley script.

The chosen algorithm for script recognition is Convolutional Neural Network (CNN). The methodology involves training the CNN model on datasets containing samples of the Phoenician, Brahmi, and Indus Valley scripts. The model is utilized for symbol recognition and analysis within the scripts.

The accuracy achieved in the analysis ranges from 94% to 99.35%, indicating the effectiveness of the CNN algorithm in accurately recognizing and differentiating the symbols from these ancient scripts.

The primary focus of the methodology is on script recognition and subsequent data analysis to determine the similarities and differences between the Phoenician, Brahmi, and Indus Valley scripts. The analysis conducted suggests a stronger similarity between the symbols of the Phoenician alphabet and the compared symbols.

In their current research, Narang et al. focus on recognizing ancient documents written in the Devanagari script. Two feature extraction techniques are used in the methodology described in [11] to extract features from Devanagari ancient manuscripts: DCT (Discrete Cosine Transformation) zigzag features and HOG (Histogram of Oriented Gradients).These features are then used for document recognition.

The accuracy reported for this system is 90.70%, indicating a successful recognition rate for the Devanagari ancient manuscripts.

The methodology includes the steps of feature extraction using DCT zigzag features and HOG, followed by training and testing using machine learning algorithms. Indeed, this approach facilitates the accurate processing of Devanagari script in ancient manuscripts.

In their research paper [12], Sharma et al. present a comprehensive survey that explores the application of machine learning techniques in recognizing handwritten Devanagari and Gurmukhi scripts, both of which are North Indian scripts. This study aims to present a comprehensive overview of the research conducted in this field, highlighting the key aspects of the domain.

The survey covers multiple algorithms, including Support Vector Machine (SVM), Probabilistic Neural Network (PNN), Convolutional Neural Network (CNN), and Extreme Learning Machine (ELM).These algorithms have been utilized in various studies for script recognition.

The methodology of the paper [12] involves comparing and evaluating the performance of these algorithms in the context of north Indian script recognition. The comparison may consider factors such as accuracy, computational efficiency, training time, and robustness.

Through conducting a comprehensive survey and comparing the performance of various machine learning algorithms, the research paper aims to provide insights into the advancements and challenges in north Indian script recognition. This can contribute to the development of more accurate and efficient techniques for recognizing handwritten Devanagari and Gurmukhi scripts.[12]

The research focuses on Malayalam Palmleaf Manuscripts and utilizes Convolutional Neural Networks (CNN) and Contrast-based Adaptive Binarization for the recognition process. The accuracy achieved is not provided in the given information.[13]

The methodology consists of multiple steps. Initially, the training and testing images undergo preprocessing and segmentation techniques to enhance the quality of the manuscript images. This step primarily aims to improve the clarity and legibility of the text.

Following that, Convolutional Neural Networks (CNNs) are employed specially designed for image analysis, are utilized for the recognition task. CNNs are employed to extract meaningful features from the preprocessed manuscript images and learn patterns relevant to the task.

After the CNN-based recognition, mapping is performed to associate the recognized characters with their corresponding textual representations. This mapping process helps convert the recognized characters into a text format.

Finally, the results are stored in a text file, allowing for easy access and further analysis of the recognized Malayalam Palmleaf Manuscripts.

The methodology outlined in the research paper by Sudarsan et al [13] combines image preprocessing, segmentation, convolutional neural networks, mapping, and text file generation to achieve recognition of Malayalam Palmleaf Manuscripts.[13]

In their work, Shahkolaei et al. [14] propose the establishment of a Multi-distortion Historical Document Image Database (MHDID). The main goal is to aid research in analyzing historical documents. The objective of this database is to support studies and advancements in the field of historical document image processing.

The primary goal is to offer researchers a standardized and diverse dataset of historical document images featuring various types and degrees of degradation. This dataset aims to provide a valuable resource for studying and analyzing historical document processing. By having access to such a database, researchers can develop and evaluate algorithms and techniques for assessing document quality and classifying the types of degradation present.

The MHDID database includes a wide range of distortions commonly found in historical documents, such as stains, tears, ink fading, and paper aging effects. The documents in the database are obtained from various historical sources, ensuring a diverse collection of images.

Researchers can utilize the MHDID database to benchmark and compare their algorithms and methodologies. The availability of a standardized database promotes consistency and enables objective evaluation of different techniques.

Overall, the proposed Multi-distortion Historical Document Image Database (MHDID) serves as a valuable resource for researchers in the field of historical document image processing. The database facilitates research efforts aimed at assessing document degradations and enables the development of effective methods for their classification [14].

This research paper by Bhat et al [15] presents a model for the enhancement and binarization of historical epigraphs, focusing on improving the quality and readability of these images. The model utilizes specific techniques such as preprocessing using phase congruency and background removal using Gaussian mixture estimation.

The proposed methodology begins with preprocessing the historical epigraph images using phase congruency. This technique helps enhance the image quality by emphasizing important features and reducing noise. By applying phase congruency, the model aims to improve the clarity and readability of the epigraphs.

After preprocessing, the model addresses the issue of background removal using Gaussian mixture estimation. This technique helps separate the foreground, which contains the desired epigraph content, from the background. By accurately estimating the Gaussian mixture, the model effectively separates the foreground and background, resulting in improved contrast and easier binarization.

While the specific accuracy of the proposed model is not explicitly stated, its main goal is to enhance and binarize historical epigraphs to improve readability and preserve the content.

In summary, this research [15] proposes a model that focuses on enhancing and binarizing historical epigraph images. The model utilizes preprocessing techniques such as phase congruency to improve image quality and background removal using Gaussian mixture estimation to separate foreground and background. Although the accuracy is not specified, the primary goal is to enhance the historical epigraphs and make them more legible for further analysis and preservation.

Weldegebriel et al. [16] focus on addressing the challenge of recognizing handwritten Ethiopian characters. The specific language involved is Handwritten Ethiopian. To address this challenge, a combination of methodologies has been employed, including Convolutional Neural Networks (CNN), XGBoost, Feature Extraction, and Pattern Recognition. The overall accuracy achieved in this recognition task is reported to be 99.84%. The proposed methodology for this project involves the integration of CNN and XGBoost algorithms. The prime advantage of this work is its accuracy but on the other hand the system perrforms slow processing. [16]

The work by Menon et al [17] involves noise removal from handwritten manuscripts. The manuscripts are written in a handwritten language. To tackle this issue, the Gibbs Sampling Algorithm and Circle Hough Transformation have been utilized as algorithms. The proposed methodology for this project revolves around the application of the Gibbs Sampling Algorithm and Circle Hough Transformation techniques to remove noise from the handwritten manuscripts. They have only worked on noise removal technique but not in the prediction of new text.

The objective of the survey paper [18] is to explore the different techniques used by users for extracting text from images.[18] It aims to provide insights into the existing approaches while identifying the gaps in these methods. Additionally, the survey includes quantitative comparisons among various different approaches and techniques for extraction of text. It also incorporates script-level comparisons, considering different writing systems. Overall, the survey aims to gather comprehensive information about the techniques employed by users for text extraction from images and highlight areas for improvement and further research only.

In their paper [19], Singh et al. address the task of segmenting a document image text into its essential components, such as text lines, words, and individual characters or sub-characters. The specific language considered is Handwritten Brahmi Script. The proposed methodology for this task includes several steps. First, LINE SEGMENTATION using MATLAB is performed to segment the text into individual lines. The document image text segmentation process involves sequential steps. The initial step involves segmenting the text lines into words, followed by a subsequent segmentation of the words into individual characters. In cases where connected characters are present, a specific technique is applied to separate them into distinct characters. Unfortunately, the available information does not mention the accuracy of the segmentation process. The overall methodology revolves around identifying and isolating the various components of the document image. The paper has only focussed on the analysis of segmentation methods. The advantage is that it focusses on through study of Brahmi script recognition.

The paper wrote by Demilew at al focusses on the recognition of the Ancient Geez script, specifically in its handwritten Ethiopian form, using deep learning techniques.[20] The chosen algorithm for this task is Convolutional Neural Networks (CNN). The methodology involves several steps. Firstly, image acquisition is performed to obtain the handwritten script images. The pre-processing phase includes several essential steps such as converting to grayscale, removing noise, binarization, and detecting/removing skew. Subsequently, line segmentation and character segmentation techniques are employed to isolate individual lines and characters within the script. Feature extraction is achieved through the utilization of convolutional layers, filters, and max-pooling. Lastly, a densely connected layer is used for classification. The reported accuracy achieved by this approach is 99.39%. The overall methodology focuses on acquiring, preprocessing, segmenting, extracting features, and classify the Ancient Geez script, deep learning techniques can be employed. The Geez script used here is available is well formed in nature so accuracy is good. But the primary challenge will be to extract and read the handwritten characters.

The survey work by Chendage et al [21] specifically focusing on Marathi language inscriptions.[21] The chosen algorithm for this task is Optical Character Recognition

(OCR). The objective is to develop a system capable of automatically recognizing and converting the text from stone inscriptions written in the Marathi script into machine-readable text. The OCR algorithm is applied to extract the characters and words from the stone inscriptions, enabling their recognition and subsequent analysis. The overall goal is to bridge the gap between ancient stone inscriptions and digital text, facilitating easier access and preservation of historical information encoded in the Marathi script on stone surfaces. This is a survey conducted for Devanagari script for Marathi language. There are many changes present between Devanagari and Brahmi script used for Marathi writing.

The survey paper by Babu et al is based on character recognition in historical handwritten documents.[22] The survey aims to explore various approaches used for character recognition in this context. The survey provides insights into the performance of these algorithms for character recognition in historical handwritten documents. These results indicate that the Feed Forward Neural Network and the Advanced Recognition algorithm achieved the highest accuracy rates among the mentioned algorithms.

The research paper by Wickramarathna et al focuses on the post-processing phase of OCR character recognition for the conversion of Bramhi characters to meaningful Sinhala sentences.[23] The proposed system aims to address OCR errors and improve word identification. The specific language pair considered is Bramhi to Sinhala.

The methodology combines Natural Language Processing (NLP) with Optical Character Recognition (OCR) and OCR correction methods. The OCR error correction module includes several components:

1. Morphological Analysis: Analyzes the morphology of the recognized Brahmi character array to identify potential errors and their possible corrections.

2. Permutations Generation Module: It generates various permutations of the identified errors to explore different correction possibilities.

3. Minimum Edit Distance Approach: The minimum edit distance is calculated between the identified errors and the possible corrections to determine the most likely corrections.

4. Best Suggestion Module: This module selects the best suggestion based on the calculated minimum edit distance and other criteria.

5. Generate Word Sequences: The system generates meaningful Sinhala word sequences from the corrected Bramhi character array using bigram and trigram models.

The accuracy reported for the system ranges from 86% to 91%. The methodology utilizes NLP techniques, OCR correction, and linguistic models to transform Bramhi characters into coherent Sinhala sentences. This approach effectively addresses OCR errors and enhances word identification scoring.

Gorge et al. [24] provide a comprehensive study for the recognition of handwritten MODI Script [24] It also includes an evaluation and comparison of these techniques.

The language of focus is Handwritten MODI Script, and several algorithms have been employed for recognition. These algorithms include Decision Tree with an accuracy of 97.68%, Euclidean Distance with an accuracy of 88.76%, Support Vector Machine with an accuracy of 77.36%, K Nearest Neighbors with an accuracy of 77%, and Backpropagation Neural Network with an accuracy of 66%.

The methodology adopted in this research comprises multiple stages. In the initial stage , In addition, pre-processing techniques are employed to enhance the quality of the handwritten MODI Script. This includes steps like noise removal, normalization,image enhancement.

Next, the pre-processed images are segmented to isolate individual characters or components for further analysis. This step helps in distinguishing and extracting meaningful units from the script.

Feature extraction techniques are then employed to extract relevant information from the segmented components. These features could include shape, texture, or statistical characteristics that represent the unique properties of the MODI Script.[24]

The extracted features are then utilized for classification using a range of algorithms, like Decision Tree, Euclidean Distance, Support Vector Machine, K Nearest Neighbors, Backpropagation Neural Network. Each algorithm is evaluated based on its accuracy in recognizing the MODI Script.

Finally, post-processing techniques may be applied to refine the recognition results, such as error correction or text normalization.

The objective of this research paper, as outlined in [24], is to advance the recognition methods for handwritten MODI Script by presenting an overview, evaluation, and comparison of different feature extraction and classification techniques.

The work proposed by Nilupuli Wijerathna et al. [25] is centered around the recognition of ancient Brahmi characters found in inscriptions dating back to the time between the 3rd century B.C. and the 1st century A.D. The proposed methodology involves several steps to achieve accurate recognition and interpretation of the inscriptions.

The first step in the methodology is to remove noise and improve the inscription image . Image processing techniques are utilized to segment and convert the individual elements into a binary representation.

Once segmented, the subsequent task involves addressing broken or incomplete characters. To achieve this, deep learning is utilized through Convolutional Neural Networks (CNNs). The CNN model is trained to accurately identify and classify the Brahmi script letters.

In addition to recognizing the letters, the methodology also aims to identify the time period of the inscriptions. This information is obtained through analysis and interpretation of the inscription content. The identified time periods are then stored in a database for further reference.

Furthermore, the system performs the translation of the recognized Brahmi letters into modern Sinhala letters, producing the desired output. This translation allows for the interpretation and understanding of the meaning conveyed by the inscriptions. NLP techniques aid in facilitating the translation process during this step.

The methodology combines image processing, deep learning (CNN), and Natural language processing (NLP) is employed to achieve recognition, interpretation, and translation of ancient Brahmi inscriptions. However, the specific accuracy of the CNN model and the overall system is not disclosed in the provided information. This integrated approach demonstrates the potential for effective analysis and understanding of the ancient script.

In summary, this research paper proposes a methodology for recognizing and interpreting ancient Brahmi characters found in inscriptions. The methodology involves preprocessing the image, segmenting the letters, recognizing the Brahmi script using CNNs, The tasks include identifying and translating the inscriptions into modern Sinhala. The system integrates image processing, deep learning, and natural language processing techniques to accomplish the recognition, interpretation, and translation tasks [25].

In the work by Assael et al, PYTHIA is the first model developed for restoring missing characters in damaged ancient Greek epigraphic texts. It utilizes deep neural networks and a methodology called PHI-ML to accomplish this task [26].

The PHI-ML algorithm forms the basis of the restoration process. It involves training a deep neural network model, named PYTHIA, to learn patterns and relationships from a dataset of intact and undamaged ancient Greek epigraphic texts. The trained model plays a crucial role in predicting the missing characters within texts that have been damaged or are incomplete. By leveraging the knowledge and patterns learned during training, the model can make educated guesses and fill in the gaps, reconstructing the original content to the best of its ability.

The accuracy of the PYTHIA model is reported to be 73.5%. This indicates its ability to effectively restore missing characters and improve the legibility and comprehensibility of damaged ancient Greek texts.

The methodology involves feeding the damaged text input into the PYTHIA model, which employs the learned patterns and relationships to predict the missing characters. The restored text is then generated as the output, providing a reconstructed version of the original damaged text.

Overall, the development of PYTHIA and the PHI-ML algorithm offers a significant contribution to the field of ancient text restoration. By using deep neural networks and a trained model, it becomes possible to recover missing characters and enhance the readability and understanding of damaged ancient Greek epigraphic texts [26].

In the experimental study conducted by Kesiman et al. [27], the main emphasis is placed on recognizing Balinese manuscripts inscribed on palm leaves. The researchers explore methods and techniques to accurately identify and interpret the content of these historical documents, contributing to the preservation and understanding of Balinese cultural heritage. The research explores the use of image-based feature extraction methods to recognize isolated word segment images. Notably, the study aims to achieve word recognition without relying on character-by-character recognition or OCR-transliteration techniques. By directly recognizing word segments, the methodology bypasses intermediate steps. This research highlights the potential of utilizing feature extraction methods and neural networks for word recognition in Balinese palm leaf manuscripts.

The survey work by Chendage et al [28] specifically focusing on Marathi language inscriptions.[28] The chosen algorithm for this task is Optical Character Recognition (OCR). The objective is to develop a system capable of automatically recognizing and converting the text from stone inscriptions written in the Marathi script into machine-readable text. The OCR algorithm is applied to extract the characters and words from the stone inscriptions, enabling their recognition and subsequent analysis. The overall goal is to bridge the gap between ancient stone inscriptions and digital text, facilitating easier access and preservation of historical information encoded in the Marathi script on stone surfaces. This is a survey conducted for Devanagari script for Marathi language. There are many changes present between Devanagari and Brahmi script used for Marathi writing.

Joseh et al. [29] focus on character recognition in the MODI script using a CNN autoencoder in their research paper. The MODI script serves as the target language for recognition.

The methodology consists of several steps. Firstly, the input image of the MODI script is provided as the starting point.

Image augmentation techniques are applied to enhance the dataset and increase its diversity.

Next, a randomly transformed batch of images is generated from the augmented dataset. This step helps in creating a more varied and robust training set.

Features are extracted from the transformed batch of images using a CNN autoencoder. The autoencoder's architecture enables encoding and decoding of input images, generating compressed representations of the features. The Support Vector Machine (SVM) algorithm is applied for classification in this context.

The implemented method demonstrates a reported accuracy of 99.3%, showcasing the feature extraction method and the combined use of CNN autoencoder and SVM for character recognition in the MODI script.

In summary, the research paper introduces a methodology for recognizing characters in the MODI script. The methodology involves using a CNN autoencoder for feature extraction and SVM for classification. The method demonstrates high accuracy in recognizing MODI script characters, indicating its potential for practical applications in text recognition and analysis.[29]

In their paper, Susan et al. [30] introduce a novel approach to deep structure learning The research focuses on the Devanagari script. The methodology involves training individual convolutional neural networks (CNNs) on five image quadrants and learning hidden state activations derived from these networks.

The first phase of the learning module focuses on training CNNs on individual image quadrants. This allows the networks to specialize in learning features specific to each quadrant. The hidden state activations from these CNNs are extracted and used.

In the second phase, a deep neural network is utilized to learn the hidden state activations obtained from the five CNNs. These activations are fused together through concatenation, allowing the network to capture comprehensive information from all the quadrants. The deep neural network is trained to recognize and classify characters based on the fused hidden state activations.

The deep structure learning approach outperforms existing state-of-the-art methods in the recognition of the Devanagari script, showcasing superior performance. While the specific accuracy of the model is not provided in the given information, the experiments show improved performance compared to previous approaches.

In summary, this research presents a novel approach to deep structure learning for handwritten character recognition in the Devanagari script. The methodology involves training separate CNNs on image quadrants and learning hidden state activations. The activations obtained from the five CNNs are combined and utilized to train a deep neural network for the purpose of character recognition. The approach shows superior performance compared to existing methods, although the specific accuracy is not mentioned [30].

Damayanti et al. [31] conducted a study with the primary objective of extracting individual characters from the manuscript. They employed an algorithm to achieve effective character separation.

The study specifically targets the Javanese language and its script. The researchers start by considering the manuscript and applying preprocessing techniques to improve the image quality. Binarization is then performed to convert the image into a binary format, which aids in subsequent analysis.

To further enhance the characters, a bold writing technique is applied. This technique emphasizes the strokes and structures of the Javanese characters, making them more distinguishable for segmentation.

The connected component labeling algorithm is then employed to identify and separate the individual characters. This algorithm is effective in isolating each character by detecting and labeling the interconnected regions within the binary image.

Through this process, the researchers successfully segment the Javanese characters in the ancient manuscripts. The achieved accuracy of the character segmentation method is reported as 80.9%.

Overall, This study offers a valuable contribution to the field of character segmentation in Javanese manuscripts, offering insights into the algorithmic techniques used to extract individual characters from interconnected regions and laying the foundation for further analysis or processing of the segmented Javanese script [31].

The study conducted by Samarajeewa et al [32] focuses on the preprocessing of archaeological images using pixel-level processing algorithms. The goal is to enhance the quality and extract relevant information from the images to aid in further analysis and interpretation.

The methodology begins with the thresholding of the archaeological images to obtain a binarized version of the image. Thresholding is a technique that separates the foreground objects from the background by selecting an appropriate threshold value. This step helps in simplifying the image and isolating the objects of interest.

The binarization process converts the image into a binary representation, where each pixel is assigned either a black or white value based on its intensity or color. This step helps in emphasizing the structural details and reducing the complexity of the image. The accuracy of the preprocessing step is reported as 76%, indicating the effectiveness of the employed pixel-level processing algorithms in achieving the desired results.

The specific pixel-level processing algorithms used in the study are not mentioned, but they likely involve techniques such as intensity normalization, noise reduction, edge detection, contrast adjustment, or morphological operations. These algorithms are applied to enhance the image quality, remove noise or artifacts, and improve the overall visual appearance.

By preprocessing the archaeological images, researchers aim to create a more suitable and standardized dataset for further analysis. The processed images can then be utilized for tasks such as object detection, feature extraction, pattern recognition, or other forms of image analysis to gain insights into the archaeological content.

In summary, this study focuses on preprocessing archaeological images using pixel-level processing algorithms. The methodology involves thresholding the images to obtain binarized versions. The accuracy of the preprocessing step is reported as 76%. The preprocessing step aims to enhance the image quality and facilitate further analysis and interpretation of the archaeological content [32].

The research by Saxena et al [33] aims to enhance the accuracy of preserving historical handwritten Devanagari documents. By utilizing a combination of HOCR and Convolutional Neural Network (CNN) techniques, an impressive accuracy rate of 97.4% is achieved. In the proposed methodology outlined by the study conducted by Damayanti et al, the first step is to extract the text from historical documents using HOCR (Hierarchical Optical Character Recognition) techniques. HOCR is a standard format for representing OCR results along with their hierarchical structure. This allows for the extraction of text content and layout information from the documents.

Once the text is extracted, the next step involves training a Convolutional Neural Network (CNN) model for Devanagari character recognition. CNNs are a specialized form of deep learning algorithms renowned for their exceptional capabilities in image recognition tasks. Harnessing the strength of neural networks, the model undergoes training on a dataset comprising handwritten Devanagari characters to grasp the intrinsic patterns and distinctive features that differentiate various characters from one another. Through this learning process, the model becomes adept at accurately recognizing and classifying the handwritten characters in the Devanagari script.

The study emphasizes the significance of preserving historical documents for future accessibility. Historical documents contain valuable information about our past, and preserving them in digital form ensures their long-term accessibility and prevents further deterioration. The use of neural network techniques, such as CNNs, in document preservation demonstrates the potential for achieving accurate recognition and preservation of historical texts .The utilization of a robust dataset further contributes to improving accuracy.

In the study conducted by Gautam et al. [33], the primary aim is to create a deep convolutional neural network (CNN) with dropout for recognizing Brahmi words. The proposed methodology revolves around the utilization of a specialized deep CNN architecture tailored for Brahmi word recognition tasksThe researchers conduct experiments using a standard Brahmi dataset to assess their proposed model.

The deep CNN architecture is designed to effectively learn and extract discriminative features from the input Brahmi word images. The incorporation of dropout regularization helps in preventing overfitting and improving the generalization ability of the model. By training and fine-tuning the deep CNN using the provided dataset, the model learns to recognize and classify Brahmi words accurately.

The trained model is tested on the established Brahmi dataset using performance metrics such as accuracy, precision, recall, and F1-score for assessment, allowing a thorough evaluation of the recognition ability for Brahmi words. The experimental results from this evaluation provide valuable insights into the potential and capabilities of the deep CNN architecture for accomplishing Brahmi word recognition tasks.

The CNN architecture comprises several layers. The initial layer consists of a convolutional layer, which is succeeded by a subsampling (pooling) layer. This pattern of convolution and subsampling is repeated in subsequent layers, with the fourth layer also being a subsampling layer. The final layer integrates the extracted features from the previous layers.

The accuracy achieved by this approach is reported as 92.47%, indicating its effectiveness in recognizing Brahmi words. Dropout is an effective regularization technique used in deep learning models like CNNs to prevent overfitting and improve generalization. The mechanism operates by randomly deactivating a fraction of neurons during the training process, creating redundancy and promoting the acquisition of resilient features. This dropout technique aids the model in effectively adapting to new, unseen data and mitigates the potential of simply memorizing the training data. Overall, the proposed deep CNN model demonstrates promise for accurately recognizing Brahmi words in various applications. [33]

The work of Mahajan et al [34] focusses on the recognition of characters in Indian handwritten script, using deep learning techniques.[34] The handswriting is in a general handwritten form. The algorithm utilized for this task is the Convolutional Neural Network (CNN) algorithm, known for its effectiveness in image recognition tasks. The methodology includes various steps such as pre-processing the handwritten script, segmentation to isolate individual characters, and data augmentation techniques to enhance the training data. The core approach is centered around the implementation of a CNN model for accurate character recognition in Indian handwritten script. The effectiveness of CNN is good but the challenge is to apply this method specially for Brahmi script.

Jayanthi et al. proposed a methodology for categorizing ancient inscription images based on the material used in creating them. Their approach involves employing image processing techniques and machine learning algorithms to analyse visual characteristics and patterns specific to different materials, including stone, metal, or clay. Feature extraction from the images is performed, followed by the application of classification algorithms, resulting in accurate classification outcomes. The study emphasizes the significance of considering material composition as a crucial factor in effectively categorizing ancient inscription images.[35] The specific language of the inscriptions is not provided. The algorithms utilized for this task include GLCM (Gray Level Co-occurrence Matrix), KAZE, BRISK, and texture classification techniques. The methodology comprises feature extraction from the inscription images using these algorithms. For the classification task, Support Vector Machines (SVM) are utilized. The focus is on extracting relevant features from the images and utilizing SVM for accurate classification based on the material of the ancient inscriptions. The material is on prime focus in this paper but the inscription part can be taken to reading the handwritten scripts.

In the work by Premi et al [36], the objective is to develop a higher accuracy model and a faster computational method for recognizing handwritten characters in English, specifically written on palm leaf.[36] The chosen algorithm for this task is Convolutional Neural Network (CNN), known for its effectiveness in image recognition tasks. The methodology encompasses various stages. The process starts with acquiring the data, followed by implementing pre-processing techniques to improve the quality of the palm leaf images. Segmentation is then performed to isolate individual characters. Finally, the CNN model is applied for character recognition. The accuracy achieved by this approach is not specified in the provided information. The overall methodology focuses on acquiring, pre-processing, segmenting, and employing CNN for accurate and efficient recognition of handwritten characters on palm leaf surfaces.

Ezhilarasi et al. [37] proposed a study to address the challenges associated with segmenting and classifying ancient words in the Palaeographic 11th century stone inscription script Their methodology primarily concentrates on the development of a model for POS Tag Classification and Word Prediction.

The language used in this research is Palaeographic, specifically focusing on the 11th century stone inscription script. Ezhilarasi et al. [37] proposed a study to address the challenges associated with segmenting and classifying ancient words in the Palaeographic 11th century stone inscription script. Their approach primarily revolves around the development of a Neural Model that aims to classify Part-of-Speech (POS) tags and predict words.

The accuracy achieved in this work is reported to be 96.43%. The methodology encompasses several steps:

1. Recognizing the historical character sequence: The initial step involves identifying and recognizing the sequence of historical characters from the inscription script.

2. Translating the character sequence: The recognized character sequence is then translated into readable words based on synthetic semantic and linguistic rules.

3. Recognizing words based on rules: Using these rules, the words in the translated sequence are recognized and segmented.

4. Discriminative classification: The words are then subjected to discriminative classification, which involves assigning appropriate POS tags to each word.

5. Word embedding and one-hot encoding: The words are vectorized using techniques such as word embedding and transformed into one-hot encoded vectors. Padding sequences are applied to ensure consistent input dimensions.

6. Classification and prediction: The classified and encoded words, along with their lemmas, are used to classify and predict the POS tags of the words in the inscription script.

The proposed methodology incorporates various techniques, including historical character recognition, word translation, rule-based word recognition, discriminative classification, word embedding, and one-hot encoding, to achieve accurate results [37].

The CNN model proposed by Deshmukh et al [38] follows a specific structure that consists of several layers designed to extract features and classify handwritten Modi document images. The model architecture can be summarized as follows:

1. Input Layer: The model initiates with an input layer designed to accept the Modi document image as input. This input layer acts as the entry point for the data into the neural network, allowing it to process the information and pass it on to subsequent layers for further analysis and feature extraction.

2. Convolutional Layers: The input image undergoes convolutional layers with (ReLU). These layers utilize filters to analyze the input image, capturing local patterns and distinctive features. The ReLU activation function introduces non-linearity, enabling the model to learn intricate representations and improve its ability to recognize more complex patterns and structures in the data.

3. Pooling Layers: After each convolutional layer, pooling layers are applied. The mentioned layers, such as the pooling and subsampling layers, are responsible for reducing the spatial dimensions of the feature maps while retaining the most crucial information. This reduction helps to condense the data and focus on the essential features, aiding the model in processing and recognizing patterns effectively. Pooling helps to abstract and summarize the learned features, making the model more robust to variations in the input.

4. Classification Stage: Following the convolutional and pooling layers, the model enters the classification stage. Here, a flattening operation is performed, which reshapes the multi-dimensional feature maps into a vector. This vector is then connected to fully connected layers, which perform high-level feature extraction and classification. The ReLU activation may be applied to the fully connected layers as well.

5. Output Layer: The output is designed as a softmax, producing probability scores for various classes or categories. In the context of recognizing handwritten Modi characters, this layer would consist of multiple units representing different Modi characters. The softmax function ensures that the predicted probabilities for these characters add up to 1, making the final classification decision.

By adhering to this particular structure, the CNN model becomes proficient in learning and extracting pertinent features from the input Modi document images. This capability facilitates precise classification and recognition of the handwritten characters.

The accuracy achieved by this system is reported as 94.6%, indicating its effectiveness in recognizing and digitizing the ancient Tamil-Brahmi script. Additionally, the translation component provides the capability to convert the recognized script into modern Tamil, further enhancing the utility of the system.

In the model proposed by Kesiman et al [39], a character recognition system is developed with the objective of digitizing the ancient Tamil-Brahmi script. The system also includes a translation component to convert the recognized script into modern Tamil. The methodology combines NLP (Natural Language Processing) and CNN (Convolutional Neural Network) architecture. This hybrid approach leverages the strengths of both NLP and CNN to effectively process and analyze the data, enabling the model to achieve accurate and meaningful results in the task at hand.

The research by Mukerem et al [40] aims to develop a model for recognizing digit and punctuation mark script in handwritten Amharic. The goal is to integrate this research with previously done handwriting text character recognition to create a complete handwriting character recognition system for the Amharic language.

The proposed methodology utilizes CNN (Convolutional Neural Network) and HCR (Handwriting Character Recognition) techniques. The model takes a preprocessed image of size 32 by 32 pixels as input.

The model uses multiple convolutional layers and max pooling operations to extract features from the input image. The initial convolutional layer extracts features from the image, and the resulting feature map is then downsampled using max pooling to reduce the spatial dimensions while preserving important information.

This process is repeated in subsequent convolutional layers, each followed by max pooling. These layers are designed to capture and extract hierarchical features from the input image.

The reported accuracy of the proposed model is 0.7004, demonstrating its capability to recognize digit and punctuation mark script in handwritten Amharic with satisfactory performance. This accuracy measure reflects the model's ability to correctly classify and identify these specific characters.

By developing this model, future researchers can integrate it with existing handwriting text character recognition systems for Amharic, thereby enhancing the overall accuracy and capabilities of the recognition system. This integration would enable comprehensive recognition of the complete range of handwritten characters in the Amharic language.

In summary, this research proposes a model using CNN and HCR techniques for recognizing digit and punctuation mark script in handwritten Amharic. The model achieves an accuracy of 0.7004 and serves as a valuable contribution towards developing a complete handwriting character recognition system for the Amharic language.[40]

3. Summary of Existing Work

It is seen from the experimentation that from the last 20 years many researchers have tried the available algorithmic approaches for finding solutions of optical character recognition methods for stone inscriptions. Very few have worked on Brahmi script recognition systems. When we summarize the same, we can find that algorithmic methods have evolved over the time with their speed and accuracy.

Period	Techniques / Approaches	Methods
2002 – 2009	Time-Series	Dynamic Time Warping (DTW)
	Supervised Machine Learning	K-Nearest Neighbors (KNN)
		Support Vector Machines (SVM) Decision Tree (ID3)
	Unsupervised Machine Learning	Hidden Markov Models (HMMs)
2010 – 2016	Deep Learning	Convolutional Neural Network
		Recurrent Neural Networks
	Ensemble Machine Learning	Random Forest
		Gradient Boosting
	Sequence Classification	Connectionist Temporal Classification (CTC)
2017 - 2024	Deep Learning	Deep Convolutional Neural Network Recurrent Neural Networks (RNN) with LSTM, GRU

The methods used in the first era were based on machine learning approaches whose speed was not up to the mark. But in the middle generation when machine learning systems are evolved that you will see improvement and speed is also increased. It is observed that the accuracy was around 90% and more. In the recent generation of OCR systems deep learning methodologies were used where datasets were larger and algorithms were also efficient. The accuracy is moved beyond 90% with moderate speed and efficiency.

4. Conclusion

This proposed work has provided a comprehensive analysis of OCR systems tailored for Brahmi script and other stone inscriptions. The unique challenges posed by the complex structure and variations of Brahmi script with other ancient scripts have been explored, along with advancements in image preprocessing, segmentation, character recognition, and linguistic analysis. Researchers and professionals in the field can now leverage this survey as a valuable resource to further enhance the digitization, preservation, and analysis of Brahmi script stone inscriptions. The findings obtained from this survey will add to a more profound comprehension of the cultural and historical importance of these antiquated documents, guaranteeing their availability for scholarly exploration and future generations.

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