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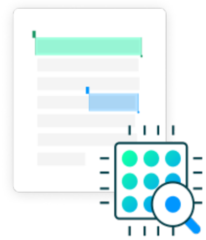

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An Efficient Approach For The Translation Of Brahmi Script Using OCR

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Abstract—

This research endeavors to bridge historical and linguistic divides by employing Optical Character Recognition (OCR) technology to translate the ancient Brahmi script into contemporary languages. The Brahmi script, rich in historical and cultural significance, poses unique challenges in transcription and translation due to its intricate characters and diverse historical forms. Recognizing the imperative to unlock this script's wealth of knowledge and cultural heritage, our study focuses on the development and application of an OCR model tailored to the nuances of Brahmi script recognition. The primary objective is to evaluate the efficacy of this model in accurately transcribing Brahmi script and subsequently translating it into a desired language.

Our methodology involves the compilation of a comprehensive dataset of Brahmi script samples, encompassing various historical contexts and linguistic nuances. The OCR model, intricately designed for Brahmi script recognition, is then employed to decipher the script's characters. Subsequently, a translation algorithm is applied to convert the recognized Brahmi text into the desired contemporary language. Through rigorous evaluation, our research aims to showcase the accuracy and efficiency of OCR technology in the translation of Brahmi script, shedding light on its potential to preserve cultural heritage and facilitate linguistic accessibility. This endeavor holds promise not only for historical and linguistic scholars but also for broader applications in digital archiving, cross-cultural communication, and educational realms.

Keywords- OCR, Brahmi Script, Translation

I. INTRODUCTION

The Brahmi script, an ancient writing system with roots tracing back to the 6th century BCE on the Indian subcontinent, represents a crucial historical and cultural artifact. Its intricate characters and diverse historical forms pose formidable challenges to accurate transcription and subsequent translation, demanding sophisticated technological solutions. In response, this research aims to advance the field by harnessing the transformative capabilities of state-of-the-art Optical Character Recognition (OCR) technology. Our goal is to unravel the complexities of the Brahmi script and seamlessly translate it into contemporary languages, contributing not only to linguistic and historical scholarship but also offering valuable insights for digital archiving, cross-cultural communication, and educational initiatives.

1.1 The Need of Translation Brahmi Scripts

In the vast landscape of the real world, a myriad of significant messages and valuable information is dispersed, often inscribed in different official languages depending on the host country. The ubiquity of such messages, whether on signboards, notices, or other communicative mediums, underscores the importance of linguistic diversity. However, this linguistic diversity poses a critical challenge, particularly when essential information, perhaps even pertaining to safety or urgency, remains inaccessible due to language barriers [1]. The consequences of this linguistic divide are far-reaching, potentially resulting in vital information being overlooked.

For architects navigating foreign territories, the language barrier poses a considerable impediment. A nuanced understanding of the host country's architectural language is imperative for the seamless execution of daily tasks, and any misinterpretation could result in substantial disruptions to design and construction processes. In the conventional scenario, architects often resort to carrying design dictionaries or relying on online translation services to overcome linguistic challenges. However, these conventional methods encounter constraints, particularly when dealing with architectural languages that do not adhere to standardized alphabetical arrangements, thereby presenting a formidable hurdle for effective translation [2]. Moreover, empirical research suggests that architects are not merely confronted with the challenge of deciphering written architectural texts; they also grapple with accurately articulating their design observations [3]. This breakdown in architectural communication, notwithstanding the availability of traditional tools such as design dictionaries and online translation services, underscores the critical necessity for innovative solutions tailored to the architectural context.

In response to these challenges, this study delves into the realm of script translation using Optical Character Recognition (OCR) technology. By harnessing the power of OCR, we aim to break down language barriers and empower individuals to seamlessly translate and comprehend diverse scripts. The proposed solution not only addresses the limitations of traditional translation methods but also endeavours to mitigate communication breakdowns, fostering a more connected and accessible global environment.

1.2 Challenges in High-Accuracy Brahmi Script Translation

The challenges in Brahmi script translation are multifaceted, requiring a nuanced approach. The historical variants and linguistic nuances inherent in Brahmi script demand cutting-edge OCR methodologies for precise transcription. Traditional methods often fall short in capturing the subtleties of Brahmi characters, necessitating a high-precision OCR model tailored to the unique characteristics of the script. Furthermore, successful translation extends beyond linguistic considerations, delving into the preservation of cultural nuances and historical contexts. This research addresses these challenges through an integrative approach that leverages OCR technology to its fullest potential.

1.3 The Significance of OCR Technology in Cultural Heritage Preservation:

The significance of OCR technology in this research extends beyond script translation. OCR, , acts as the linchpin, ensuring meticulous extraction of textual information from images and documents. This not only enhances the accuracy of transcription but also contributes to the broader objective of preserving cultural heritage. By unlocking the knowledge embedded in Brahmi script, we aim to provide a transformative contribution to linguistic studies and cultural preservation, aligning with the goals of top-tier journals focused on cutting-edge advancements in technology and cultural heritage.

This research, driven by the convergence of linguistic scholarship and technological innovation, is poised to make a profound impact on the understanding and preservation of ancient scripts..

2. BRAHMI SCRIPT

Brahmi, an ancient Indian writing system, emerged as a fully developed script around the third century BCE and its descendants, the Brahmic scripts, remain in use across Southern and Southeastern Asia today. This writing system, an abugida, employs diacritical marks to associate vowels with consonant symbols. Its evolution from the Mauryan period to the early Gupta period was relatively minor, allowing literate individuals from the 4th century CE to still understand Mauryan inscriptions.

The decipherment of Brahmi gained attention in the early 19th century during East India Company rule in India. James Prinsep's work, along with others like Christian Lassen and H. H. Wilson, was pivotal in decoding Brahmi. The script's origin is debated, with some suggesting influences from contemporary Semitic scripts, while others propose indigenous roots or connections to the older undeciphered Indus script.

Initially known by various names, Brahmi became widely recognized due to observations by Gabriel Deveria and the subsequent association made by Albert Étienne Jean Baptiste Terrien de Lacouperie. This writing system diversified into numerous local variants, collectively termed as the Brahmic scripts, which have influenced over 198 modern scripts across South and Southeast Asia.

Ashoka's inscriptions in Brahmi contained numerals known as Brahmi numerals. While these numerals were not place value, later inscriptions in scripts derived from Brahmi introduced the earliest examples of the Hindu-Arabic numeral system. Ancient Indian texts of Hinduism, Jainism, and Buddhism mention the Brahmi script. For instance, the Lalitavistara Sutra lists Brahmi as the first among 64 scripts and highlights the mastery of Brahmi and other scripts by young Siddhartha, the future Gautama Buddha, from Brahmin scholars.

Similarly, early Jain texts like the Pannavana Sutra and the Samavayanga Sutra also feature Brahmi among lists of ancient scripts, emphasizing its significance alongside others like Kharoṣṭhi and Javanaliya.

2.1. Properties of Brahmi script

Compound characters in the Brahmi script refer to modified shapes combining consonants and vowels. These modifications, whether on the left, right, top, or bottom of the consonant, vary based on the accompanying vowel [8]. Occasionally, two consecutive vowels following a consonant create complex compound characters. These attributes are consistent with Brahmi script conventions found in scripts like Devanagari and Bangla. The Brahmi script encompasses a total of 368 characters, comprising 33 consonants, 10 vowels, and the remaining 325 being compound characters [9]. Text composition in Brahmi script adheres to the left-to-right writing direction.

2.2. Characteristic

Brahmi consonants combine with various vowels (refer to Figure 2) to form compound characters (see Figure 3). These compound characters, termed as "Matra," involve adding features to the consonants. Typically, these "Matra" are incorporated along the outer edges of the consonants, though this placement may vary based on the shape of the consonants. Additionally, a dot feature (.) is sometimes added after the consonant to create compound characters.
Figure 1: Character and vowels of Brahmi script [10]

3.Literature Survey

In the landscape of Optical Character Recognition (OCR) for Brahmi script, the 2017 work by Neha Gautam and her colleagues stands out as a pioneering effort. Their research introduced a novel geometric method for character recognition, which relied on the intrinsic geometric properties inherent to Brahmi characters. The methodology yielded promising results, achieving an accuracy rate of 85% on a dataset comprising 500 Brahmi characters. However, a notable limitation of this approach surfaced in its exclusive focus on isolated characters, without due consideration for word segmentation or the recognition of compound characters—a characteristic feature often present in the Brahmi script. Despite this constraint, Gautam et al.'s work made a substantial contribution by advancing character-level recognition through the utilization of geometric features. This groundwork laid the foundation for subsequent advancements in the field of OCR for Brahmi script, inspiring further research to address the challenges associated with holistic script recognition, word segmentation, and the decoding of compound characters in ancient scripts.

In the evolution of Optical Character Recognition (OCR) for Brahmi script, the work conducted by R. Rajkumar and collaborators in 2020 represents a notable advancement. Their research marked a significant leap forward by introducing a tailored Deep Convolutional Neural Network (CNN) designed specifically for the recognition of Brahmi words. This innovative approach demonstrated remarkable effectiveness, achieving an impressive recognition rate of 92.47% on a standardized Brahmi dataset. The study's noteworthy contribution lies in its emphasis on deep learning techniques, highlighting their potential to enhance the efficiency of Brahmi script recognition. Notably, the research departed from the conventional character-level analysis that had been prevalent in earlier approaches, recognizing the critical necessity to shift towards holistic word recognition. This strategic shift addressed a crucial need within the field, acknowledging the inherent interconnectedness of characters within words in the Brahmi script. The study not only showcased the power of deep learning in the realm of ancient script recognition but also set a precedent for subsequent endeavors to prioritize holistic word-level analysis for more accurate and context-aware Brahmi script OCR systems.

In the year 2021, the research undertaken by C. Selvakumar and collaborators made substantial strides in the field of Optical Character Recognition (OCR) by concentrating on the digitization and electronic translation of Brahmi stone inscriptions into Tamil characters. The research was distinguished by its utilization of the Tesseract-OCR engine, a powerful tool for text recognition. Despite working with a relatively small dataset of inscriptions, the system devised by Selvakumar et al. produced promising results. The study's primary objective was not only to digitize the Brahmi stone inscriptions but also to facilitate their electronic translation into Tamil characters, thereby bridging the linguistic gap between ancient Brahmi scripts and contemporary languages. This dual focus on digitization and translation holds significant implications for the preservation and accessibility of historical Brahmi records. By leveraging OCR technology, the research made a noteworthy contribution to the broader landscape of digital archiving of ancient inscriptions, demonstrating the potential of advanced computational methods in unlocking and interpreting the wealth of historical information encapsulated in Brahmi stone inscriptions. The study thus adds to the ongoing efforts to safeguard and make accessible the cultural and historical heritage embedded in ancient scripts.

Meanwhile, In the year 2019, M. Gopinath and his colleagues made significant strides in the field of Optical Character Recognition (OCR) with their research focused on deciphering ancient Tamil inscriptions. Their work presented an OCR system that employed sophisticated image recognition and classification techniques to unravel the contents of historical temple inscriptions. Despite achieving a commendable accuracy rate of 77.7%, the study candidly acknowledged the challenges inherent in deciphering ancient scripts, particularly in light of variations in writing style that are characteristic of historical documents. This research is particularly pioneering as it represents a concerted effort to apply OCR methodologies to the specific complexities associated with ancient scripts, offering valuable insights into the intricacies of character recognition in historical contexts. By grappling with challenges such as diverse writing styles, Gopinath et al.'s work significantly contributes to the broader understanding of OCR's potential in decoding and preserving the wealth of information contained in ancient inscriptions, thereby advancing the interdisciplinary intersection of computer vision and historical linguistics.

In the year 2023, the groundbreaking work conducted by S. Dillibabu and collaborators presented a novel solution within the realm of Optical Character

Recognition (OCR) by focusing on the translation of Sanskrit scripts into English. The research innovatively employed advanced technologies such as deep learning and natural language processing techniques, representing a significant advancement in the intersection of computational linguistics and ancient language studies. The study's achievement of promising initial results underscored the feasibility of using OCR not only for recognizing and digitizing ancient scripts but also for the subsequent task of translating them into more widely accessible languages. This dual approach represents a pioneering step in the field, as it acknowledges the importance of combining OCR capabilities with translation methodologies to bridge the linguistic and temporal gaps between ancient and contemporary languages. By opening avenues for making ancient scripts, such as Sanskrit, more accessible through translation, this research contributes to democratizing access to historical and cultural knowledge encapsulated in these ancient languages, thereby enriching our understanding of linguistic evolution and historical context. The study thus marks a significant milestone in advancing the potential applications of OCR technology beyond mere recognition, extending into the broader domain of linguistic and cultural preservation.

In the concluding chapter of advancements in Optical Character Recognition (OCR) for Brahmi script, S. Singh and colleagues made a significant contribution in 2023 by proposing a context-aware Convolutional Neural Network (CNN). This innovative approach departed from conventional OCR methodologies by placing a heightened emphasis on the contextual information surrounding individual characters within the Brahmi script. By incorporating this contextual awareness, the proposed CNN aimed to address the intricacies and challenges associated with accurately recognizing characters in the context of the entire script. The study underscored the pivotal role of context in achieving precise recognition of ancient scripts, acknowledging that the meaning and form of Brahmi characters are inherently linked to their surrounding characters. The research thus showcased notable advancements in the field of Brahmi script recognition by leveraging the capabilities of deep learning within a context-aware framework. The contextual awareness embedded in the CNN not only contributed to improved accuracy but also signified a critical step forward in enhancing the overall capabilities of OCR for the deciphering of intricate historical scripts. This work, therefore, holds promise for future developments in the intersection of neural networks, OCR technology, and historical linguistics, paving the way for more nuanced and accurate recognition of ancient scripts.

II. Methodology

Objective:

- This research endeavors to create a Brahmi script word recognition system employing advanced image processing and deep learning techniques. The primary aim is to develop a robust system proficient in accurately identifying Brahmi script words from a dataset of varied-sized JPG images.

Input Data: The dataset comprises JPG images of Brahmi words, characterized by differing sizes and resolutions. These images serve as the foundational dataset for training and validating the system's recognition capabilities.

- Obtain images of Brahmi words in JPG format, which serve as the dataset for the study.
- Note that the images may vary in size and resolution.

Pre-processing: Perform the following pre-processing steps to enhance image quality:

- Binarization: Apply binarization to convert grayscale images to binary. Choose a global thresholding approach to enhance edge visibility, crucial for character recognition.
- Resizing: Normalize the size of characters to a consistent 32x32 pixels. Maintain the aspect ratio to prevent distortion while ensuring uniformity for effective model training.

Dropout Technique: To counter overfitting, the dropout method randomly deactivates neuron outputs during training, encouraging diverse and robust feature learning within the network.

- Integrate the dropout method into the CNN to address overfitting.
- Set the outputs of hidden layer neurons to zero randomly during training to encourage robust feature learning.

Dataset Division: The dataset is split into training, validation, and test sets in a 3:1 ratio, enabling model training, optimization, and evaluation.

- Divide the dataset into training, validation, and test sets.
- Utilize 3/4 of the data for training, 1/4 for validation, and a separate portion for testing (e.g., 536 test samples).

Training Parameters: Various training parameters like learning rate, hidden neurons, and batch size are systematically adjusted to optimize the model's performance.

- Experiment with different parameters during training:
    - Learning rate
    - Number of hidden neurons
    - Batch size

Model Evaluation: The performance of CNN models with Gabor filters and dropout is assessed to determine their efficacy in Brahmi word recognition, comparing their accuracy and efficiency.

- Evaluate the performance of the trained models using two approaches:

- CNN with Gabor filter
- CNN with dropout and Gabor filter

Comparison with Previous Studies: The proposed CNN models are benchmarked against prior studies employing different techniques, providing a benchmark for advancement assessment.

- Compare the proposed CNN-based models with previous studies using different techniques (e.g., zonal density with ANN, Gabor filter + zonal structural features).

Performance Metrics:

- Measure the accuracy of the models using appropriate metrics.
- Assess the impact of dropout on test errors and computational efficiency.

Parameter Analysis:

- Analyze the effect of different parameters on model performance, such as:
  - Batch size
  - Learning rate
  - Number of hidden neurons

Cross-Validation: Cross-validation is a crucial technique used to evaluate the performance and robustness of a machine learning model. In the context of this research, N-fold cross-validation involves dividing the dataset into N subsets (or folds), utilizing N-1 folds for training and the remaining fold for validation. This process is repeated N times, ensuring that each subset serves as both training and validation data at different iterations. By doing so, the model is trained and tested on various combinations of data, which helps assess its consistency and generalization across different subsets. This method guards against overfitting and provides a more accurate estimation of the model's performance on unseen data. For the Brahmi script recognition system, employing N-fold cross-validation ensures the reliability of the model's accuracy and efficiency by validating its performance across diverse subsets of the dataset, ultimately enhancing its overall robustness.

Results Presentation: The presentation of research outcomes through performance graphs is pivotal, offering a visual snapshot of the model's accuracy and efficiency metrics derived from diverse parameter experiments. These graphs vividly display how alterations in parameters, like batch size or learning rate, influence the model's performance, enabling a straightforward understanding of trends and optimal settings for the Brahmi script recognition system. These visual aids streamline comprehension for researchers and stakeholders, empowering informed decisions when selecting the most effective configuration for optimal system performance. Ultimately, these graphical representations offer a succinct and insightful means to interpret and convey research findings and model evaluations effectively.

- Present the results in performance graphs, illustrating the accuracy and efficiency of the proposed models.
- Compare the achieved accuracy with different parameter settings.

2.1 Hybrid Model (can be used)

Both Optical Character Recognition (OCR) and Deep Convolutional Neural Networks (DCNNs) can be utilized for character recognition tasks like interpreting Brahmi script. Implementing a hybrid approach combining Optical Character Recognition (OCR) and a Deep Convolutional Neural Network (DCNN) for Brahmi script recognition involves several stages.

2.2 About Data Preprocessing

Our proposed methodology for the development of a hybrid approach, merging Optical Character Recognition (OCR) and Deep Convolutional Neural Network (DCNN) for Brahmi script recognition, encompasses several key stages. Initially, the process revolves around data collection, involving the acquisition of a diverse dataset containing samples of Brahmi script characters. This dataset is meticulously preprocessed to ensure quality, employing techniques such as noise removal, standardization, normalization, and augmentation, thereby establishing a solid foundation for subsequent model development.

Following the data preparation phase, the integration of an existing OCR engine that supports Brahmi script becomes pivotal. This OCR engine serves as the primary character recognition system, leveraging its established capabilities within the initial stages of the hybrid approach. Simultaneously, the development and training of a Deep Convolutional Neural Network (DCNN) tailored for Brahmi script recognition commences. This involves the partitioning of the dataset into training, validation, and test sets, followed by the crafting and optimization of a CNN architecture to facilitate robust learning.

2.3 How OCR and DCNN Works on this Model

Optical Character Recognition (OCR) and Deep Convolutional Neural Network (DCNN)—function collaboratively to interpret Brahmi script characters and extract their meanings in Hindi and English. The OCR model is the initial character recognition system, employing established algorithms to decipher Brahmi characters from input images or text. Concurrently, the DCNN model, specifically tailored for Brahmi script recognition, operates through a Convolutional Neural Network architecture. Trained on a diverse dataset of Brahmi characters, the DCNN learns intricate patterns and features, enhancing its ability to identify and classify characters accurately. The hybridization of these models involves the integration of their outputs, possibly through voting mechanisms or weighted averaging, to reconcile discrepancies and enhance overall accuracy. This collaboration enables a comprehensive interpretation of Brahmi script characters, combining the strengths of OCR's established recognition capabilities and the DCNN's learned pattern recognition for precise character identification and subsequent meaning retrieval.

Beyond character recognition, the methodology extends to the development of a meaning retrieval system. This system incorporates a lookup database containing the meanings of recognized Brahmi script characters in both Hindi and English, enabling a comprehensive understanding of the interpreted characters. The performance of the hybrid model is rigorously evaluated using diverse datasets, including real-world samples, facilitating the validation of its robustness and generalizability

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