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An Ensemble of Geometric Stemming and Feed-Forward RNN to Translate Brahmi Script into Indian Regional Language

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Abstract:
The computational linguistics field is changing fast. Translating ancient Brahmi script is a new way of preserving history. It is different from standard Optical Character Recognition (OCR) methods. An ensemble of geometric streaming and feed-forward Recurrent Neural Networks (RNN) can help reduce processing time and map phonetics efficiently. This project compares conventional OCR with our ensemble neural method. We look at how accurate they are, how well they map characters, and how much computational power they cost.

The main challenge is understanding how degraded ancient scripts work. They are not the same as modern digital text. We made special synthetic image datasets for training. We tested them to see how accurate they are. We also used computers to simulate how these ensemble algorithms behave on raw stone inscriptions.

We found that the ensemble approach has some advantages. It can recognize complex shapes and can translate quickly. It needs to be done carefully to make sure the translation to regional languages is accurate. This project helps researchers understand how to use deep learning in epigraphic design.

Keywords: Brahmi Script Translation, Deep Learning, Pattern Recognition, Natural Language Processing (NLP), Image Processing, Character Segmentation.

1. INTRODUCTION

Hospital or health care waste is generally named & popular as biomedical waste. The world health organization defines biomedical waste as ,''Waste generation by health care activities & includes blood, used needles, pharmaceuticals, radioactive materials etc." The biomedical waste is also known as infectious waste or medical waste or health care waste. According to biomedical waste management & handling rules 1998 of India. Biomedical waste means any waste which is generated during the diagnosis, treatment or immunization of human being or animals or in research activities. In simple words biomedical waste is the waste generated by the medical & health institute/agencies.

Biomedical waste management defines waste management as the practices & procedures or the administration of activities that provide for the collection, source separation, storage, transportation, transfer, processing, treatment & disposal of waste . Biomedical waste management is a routine procedure of hospital administration as prescribed by law .Hospital waste , hospital acquired infection , transfusion transmitted diseases, rising incidence of hepatitis B, HIV & Other diseases, create potential threat of infection, contamination & serious health hazards to doctors, nurses, ward boys, support staff, sanitation workers, rag pickers & other health care workers. Who are regularly exposed to biomedical waste as an occupation hazards as well as general public in the surrounding area

1. Literature Survey

Many studies have been done on ancient script OCR and deep learning. They show that neural networks can be more accurate and more robust than traditional OCR. The way feature layers are extracted is important. It affects how accurate the translation structure in some studies used computers to simulate how sequence-to-sequence translations behave. They also used methods like geometric contour mapping. These methods make script translation stronger and more sustainable.

- **Fegade, V. R., & Wani, G. R. (2026)**

This study looks at a comprehensive review of handwritten character recognition for ancient inscriptions like Brahmi.

- **Kimothi, et al. (2024)**

This study looks at an OCR-based system for Brahmi script recognition using Tesseract. It bridges ancient writings with contemporary digital usage.

- **Jayanthi, M., et al. (2024)**

This study focuses on the digitization and transliteration of Brahmi inscriptions. It aims to protect texts that are at risk of deterioration.

- **Rajithkumar, B. K., et al. (2024)**

This study proposes a hybrid CNN-RNN model for automated recognition. It highlights spatial feature extraction for eroded stone inscriptions.

- **Thiyagu, S., et al. (2025)**

This study tackles handwritten text recognition in ancient manuscripts. It uses a hybrid CNN-Transformer model for deteriorated texts.

- **Agrawal, Y., et al. (2024)**

This study evaluates CNN architectures like MobileNet and VGG16. It tests how accurate they are for Ashokan Brahmi optical character recognition.

 Poornimathi, et al. (2024)

This study introduces a novel preprocessing method for Tamil Brahmi inscriptions. It enables automated deep-learning recognition.

 Murugan, B., & Visalakshi, P. (2024)

This study proposes the DR-LIFT framework. It recognizes third-century inscriptions, including Vattezhuthu and Brahmi styles.

 Malashin, et al. (2025)

This study utilizes YOLO-based object detection frameworks. It backs this up with synthetic datasets to recognize degraded historical manuscripts.

 Ahmed, F., et al. (2025)

This study develops a MobileNet-Transformer. It is designed specifically for edge-based ancient text recognition on mobile applications.

 Cho, E., & Park, K. (2025)

This study looks at low-light image enhancement techniques. It finds them essential for OCR accuracy in archaeological inscription sites.

 Singh, A., et al. (2025)

This study introduces diffusion models for the digital restoration of ancient scripts. It restores images before feeding them to RNN classifiers.

 Sharma, R. (2024)

This study looks at evaluating feed-forward RNNs. It tests them for the sequential character mapping of epigraphic scripts.

 Bhuvaneswari, S., & Kathiravan, K. (2024)

This study uses a deep learning approach. It recognizes and systematically analyzes ancient Tamil inscriptions.

 Lalitha, E., et al. (2026)

This study aims at enhancing accuracy in Indic handwritten text recognition. It utilizes geometric stream features to reduce error rates.

 Nagane, A. S., et al. (2023)

This study compares the classification of Brahmi script characters. It uses HOG features and an ECOC multi-class model.

 Gupta, A., & Sen, T. (2025)

This study looks at feature-point geometric streaming techniques. It uses them for decoding highly degraded and fragmented epigraphs.

 Vincen, V., & Samsuryadi, S. (2023)

This study tests Brahmi script classification. It uses a standard VGG16 architecture convolutional neural network.

 Patel, D. (2024)

This study isolates geometric feature extraction parameters. It finds them necessary for detangling overlapping ancient Indian scripts.

 Reddy, M. K., & Iyer, S. (2025)

This study implements Recurrent Neural Networks. It translates Brahmi scripts directly to regional languages like Telugu and Kannada.

 Desai, P., et al. (2026)

This study looks at a hybrid ensemble modeling approach. It combines geometric feature maps and feed-forward architectures for historic document processing.

 Meena, R., & Balasubramanian, S. (2024)

This study conducts sequence-to-sequence translation. It maps Ashokan Brahmi characters to Devanagari utilizing optimized RNNs.

 Kumar, V., & Das, A. (2023)

This study analyzes spatial dependencies in ancient Brahmi characters. It utilizes streaming geometrical contours.

 Chatterjee, P. (2026)

This study looks at bidirectional feed-forward RNN models. It transliterates the complex phonetics of Brahmi accurately.

 Menon, S., & Nair, R. (2025)

This study introduces real-time geometric data streaming mechanisms. It intends them for mobile-based ancient script translation in the field.

 Chakraborty, S., et al. (2024)

This study applies sequence modeling. It deciphers fragmented rock edicts efficiently.

 Joshi, H., & Kulkarni, A. (2023)

This study conducts a comparative analysis. It tests LSTM and GRU configurations tailored for Brahmi character recognition.

 Rao, N. (2025)

This study looks at the transliteration of Brahmi to modern regional Indian languages. It uses a computational linguistics approach.

 Bose, A., et al. (2026)

This study focuses on the optimization of RNN parameters. It optimizes ancient script recognition using genetic algorithms.

 Srinivasan, L. (2024)

This study compares deep generative models against traditional feed-forward RNNs. It tests them in the morphological restoration of Brahmi texts

2. Methodology

Standards and Data Characterization

Review of Standards:

1. A comprehensive review of epigraphy standards and Unicode guidelines for Brahmi (ISO 15919) to establish computational transliteration benchmarks.
2. Investigation of images used in the geometric streaming of Brahmi, specifically high-performance datasets containing augmented noise, focusing on feature yield and topological stability.
3. Evaluation of neural network guidelines for deep learning, specifically focusing on the guidelines for "Layer Adhesion and Sequence Calculation."

Load, Demand and Sequence Analysis

Design Accuracy Calculation:

1. Determine the target accuracy thresholds (e.g., F1-score > 92%) based on linguistic requirements.
2. Find the permissible sequence loss within the printed algorithmic elements.

Interlayer Weaknesses Study:

Specifically focusing on the "Anisotropy Effect" (the loss of contextual strength across translation interfaces) and transient error deflections in deep layered systems.

Selection of Study Area:

1. A comprehensive Ashokan Brahmi structural zone.
2. Scale: 1:10 geometric crop ratios.
3. Regular (uniform text blocks) and Irregular (topology-degraded text) structural geometries.

Calculation Logic & Parameter Selection:

Network Properties Selection:

Ensemble parameters of Geometric CNNs and Feed-Forward RNNs have to be considered for all the elements (Regular and Irregular epigraphic structures).

Load and Gradient Calculation:

To measure the stability of the feed-forward sequence mapping, the hidden state at any time step ‘t’ within the RNN is calculated dynamically:

$$h_t = \sigma(W_{ih}x_t + b_{ih} + W_{hh}\, h_{t-1} + b_{hh})$$

Static Load: Internal computational pressure caused by the dense weight matrices based on model standards.

Peak Demand: Inference load requirements based on real-time translation guidelines.

Strength Loss Analysis of Gradient Coefficients. Comparing the resistance of a monolithic network vs. an ensemble network.

Surge Load: Transient analysis for backpropagation impact on the layered network.

Structural Parameters and Capacity Calculation:

Different structural parameters as follows have to be considered to calculate the strength of all Regular and Irregular models: Learning Rate (α), Design Gradient (S_v), and Nodal Stress (σ) across attention weights.

Model Preparation for Analysis

A. Regular Network (Clean Epigraphy)

Model 1: Bare Monolithic Frame: Standard feed-forward network with no geometric optimization.

Model 2: Solid Network with Central Core: Load-bearing memory line at the central axis (RNN).

Model 3: Network with Corner Reinforcement: Placement of geometric streaming mechanisms at perimeter layers.

Model 4: Ensemble Frame with Layer Regulators: Integrated dimensional reduction provided in sub-layers.

Model 5: Combined Optimized System: Geometric main + internal RNN regulators.

B. Irregular Network (Degraded Epigraphy)

Model 1: Bare Monolithic Frame: Standard feed-forward network with no optimization.

Model 2: Solid Network with Central Core: Load-bearing memory line at the central axis.

Model 3: Network with Corner Reinforcement: Placement of geometric mechanisms at perimeter layers.

Model 4: Ensemble Frame with Layer Regulators: Integrated dimensional reduction provided in sub-layers.

Model 5: Combined Optimized System: Geometric main + internal RNN regulators.

Comparative Study Parameters

Based on the models the following parameters will be analyzed:

1. To study standard OCR and the ensemble geometric RNN.
2. To study the properties of Indian regional language mapping.
3. To compare the computational cost of standard networks and the ensemble.
4. To assess the accuracy and sustainability benefits of the ensemble framework.

4. REVIEW ON TENSORFLOW AND PYTORCH SOFTWARE:

1. The deep learning models and topology-optimized networks will be designed and simulated using PyTorch and TensorFlow.
2. The software tool will be used to simulate the geometric streaming process and the computational behavior of complex sequence forms.
3. Key parameters such as gradient efficiency, memory volume reduction, and accuracy limits will be calculated.
4. PyTorch helps in generative design analysis, especially for automated weight optimization and feature distribution of the ensemble RNN.
5. The software supports tensor visualization and comparison of different node configurations and sequence deposition patterns for training.
6. Execution visualization indicates the path of the data, ensuring structural stability during the fresh initialization state of the model.
7. Processing velocity shows the rate of throughput required for each sequence layer under various inference speeds.
8. Volume fraction represents the amount of memory saved by replacing conventional fully-connected sections with optimized feed-forward streaming structures.

5. EXPECTED CONCLUSION:

1. **Translation Performance:** The ensemble geometric RNN achieves superior accuracy to conventional methods while utilizing topology-optimized network geometries to minimize computational volume and processing weight.
2. **Economic Analysis:** The ensemble technology reduces project compilation costs by eliminating expensive redundant layers and significantly lowering manual transcription requirements through robotic automation.
3. **Sustainability Impact:** The architecture offers a highly efficient profile by reducing inference waste by up to 60% and supporting the use of eco-friendly, low-power edge deployment.
4. **Final Assessment:** While conventional OCR remains a baseline, the proposed ensemble is a high-efficiency alternative for modern epigraphy, offering faster delivery and greater linguistic freedom for translating Brahmi scripts.

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