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Damaged Brahmi Stone Inscriptors Text An alysis using Enhanced MobileNet Approach

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Abstract: **Digital preservation of Old Brahmi stone texts requires advanced methods to translate their contents because natural degradation combined with historical damage has affected these texts. Current image-based recognition systems face significant difficulties in studying characters from damage archaeological artifacts when the characters remain partially hidden. The research team created an improved MobileNet architecture which focuses on interpreting damaged written characters for dealing with current system restrictions. The system employs aim-specific neural network mechanisms that amalgamate multi-scaled features using dilated networks along with purpose-built activation functions during its image completion stage. The proposed system consists of complete preprocessing elements with two identification techniques: transliteration algorithms and word prediction functions that combine linguistic data and visual patterns. Due to the experimental evaluation of 70,000 Brahmi characters from hand-writing and stone-engraving our model can recognize 90% of damaged inputs outstripping standard CNN architectures by 8%. Visual features of inscription help restore damaged text fragments which allows historians and archaeologists to unravel previously indecipherable ancient Indian documents.**

Keywords: Brahmi Script Recognition, MobileNet Enhancement, Stone Inscriptions, Attention Mechanism, Transliteration, Missing Word Prediction.

1. INTRODUCTION

The deterioration of essential Brahmi stone inscriptions limits both historical preservation efforts and inscription interpretation toward cultural and linguistic tracking in the Indian subcontinent [4]. Standards recognition systems face significant challenges when processing the 3rd century BCE inscriptions since their damaged characters exhibit partial erosion and cracking and other types of deterioration [5].

The analysis of Brahmi inscriptions requires three advanced steps after traditional character recognition for both character interpretation and script conversion and damaged text recovery based on contextual analysis. According to Singh and Sharma [5], the first issue in Brahmi inscription analysis has been researched through feature enhancement methods despite needing substantial system redesign to deliver meaningful improvements. Standard convolutional neural network-based character recognition models effectively process historical specimens properly but they fail to identify actual archaeologically damaged artifacts [6].

According to Kumar et al. [4] attention mechanisms succeeded in historical document character recognition while Jangid and Srivastava [7] applied dilated convolutions for improved damaged text recognition. The standard version of CNN networks delivers 72% accuracy in Brahmi character recognition for medium damage cases but shows below 45% reading achievements when dealing with heavily deteriorated samples per Tiwari et al. [7]. The performance of conventional architectures decreases because they fail to handle visual information that lacks completion or suffers damage to its elements.

Dhanya and Venkatesh [8] studied neural transliteration approaches using proper characters though these methods fail to process actual archaeological materials efficiently. Studies conducted by Malhotra and Khare [9] prove the necessity of incorporating surrounding textual data to forecast words in ancient inscriptions.

The current difficulties identified in these challenges may be resolved effectively by machine learning architectures. Modern research about inscription analysis combines visual processing methods with textual data evaluation techniques. Raghunath and Jain constructed visual-linguistic models which enhanced archaeology inscription analysis through visual elements used for contextual interpretation [14]. This method applies as a part of current multimodal machine learning frameworks to merge compatible data platforms which enhance performance output.

2. LITERATURE SURVEY

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One of the initial comprehensive evaluations of deep learning for recognition of ancient Indic script occurred through Pal and Kushal's research [1]. Their study developed fundamental performance benchmarks for different CNN architecture designs through verifying 85-90% success rates with clear characters yet encountering significant errors when processing damaged input data. The research built significant progress but failed to resolve the specific obstacles encountered in stone inscription analysis.

The authors Choudhary and Sharma [2] studied MobileNets in historical document analysis to show how these networks improve mobile device performance. Their system showed accuracy comparable to competing approaches (88.3%) while using fewer computational resources but it did not include particular optimizations for defective characters. An improvement through attention mechanisms was proposed by the authors.

The authors Dixit and Patel [3] presented robust archaeological inscription feature extraction through the use of Gabor filters alongside local binary patterns. Standard preprocessing methods showed a 12% decrease in recognition performance for characters which experienced moderate damage but this deficit was eliminated by their new method. Their effective method depended heavily on manually created features despite lacking learned representations.

Kumar et al. applied attention mechanisms to boost the recognition of characters in historical documents that have deteriorated [4]. The network with its self-attention module paid attention to key areas of observable characters which resulted in 78.5% accuracy rates on poorly preserved samples. Their system primarily processed paper-based documents instead of stone inscribed materials.

The authors Singh and Sharma [5] have presented multi-scale feature fusion techniques for ancient script recognition. The architecture combined features obtained from different layers of the network to extract both localized fine details and structural global information. Single-scale approaches demonstrated lower accuracy levels when processing damaged characters but the researchers achieved a 9.4% enhancement in their accuracy through their experiments.

The research by Gupta et al. [6] utilized three CNN architectures named VGG16, ResNet50 and MobileNetV2 to focus on Brahmi script recognition. The study achieved 92.7% accuracy when analyzing clear photographic images from manuscript sources even though it focused on analyzing damaged stone inscriptions. Following their research establishment of stone inscription modification needs Gupta et al. (2019). failed to develop these required approaches.

Dilated convolutions demonstrate effectiveness in recognizing damaged text according to the research by Jangid and Srivastava [7]. Excessive parameters in dilated convolutional layers allowed an expansion of the text perception field while keeping identical parameter counts to boost damaged text recognition by 15.3%.

The authors Dhanya and Venkatesh [8] researched ways to use neural machine translation to convert Brahmi text into contemporary Indian script. Through the implementation of an attention mechanism the sequence-to-sequence model achieved 85.2% transliteration accuracy during their test operations. Character recognition precision acted as a preprocessing need which made the system effective for complete characters but prevented it from working well with partially visible inputs.

The scientists Malhotra and Khare [9] conducted research focused on filling gaps of unknown words in historical inscriptions by using contextual prediction methods. The predictive system made from n-gram models connected with LSTM networks predicted words with accuracy at 63.7% in small gaps but showed significant drops as the sequence gaps grew longer.

Through their study Malaviya and Chaudhuri [10] created iconographic analysis to allow researchers to better understand ancient Indian inscriptions. The integration of visual element analysis into inscriptions increased prediction accuracy for missing words according to their research results by 8.5%.

The study conducted by Gupta et al. [12] explored how CNNs benefit from residual connections for detecting damaged epigraphic materials. Their network design utilized skip connections at every level which resulted in a 11.7% accuracy boost for characters with erosion occurring at the edges. The research proved that residual connections represent a fundamental architectural requirement when performing recognition of damaged characters.

Khare and Sahu [16] conducted a study which compared traditional ReLU activations against newer activation functions Swish and Mish for the recognition of damaged characters. Both Swish and Mish provided superior performance than ReLU according to their research on deteriorated character datasets where Swish notched a 3.2% accuracy boost on extreme cases.

The authors Desai and Kumar [17] studied methods for creating and enhancing ancient script datasets for recognition purposes. Through their augmentation methods of incorporating cracks and partial character masking and texture overlays they achieved detection models with 7.8% better accuracy rates on damaged characters than those trained without damaged characters.

The researchers Raghunath and Jain [18] created visual-linguistic models which fused information about both textual and iconographic components for analyzing archaeological inscriptions. Through their method the interpretation accuracy in damaged text increased by 13.2% when iconographic elements became visible even though significant parts of the writing were missing.

Verma et al. [19] created a benchmark database for recognizing Brahmi characters which contained different levels of degradation. Their collection of stone inscription images totaling 7,500 consisted of five degradation levels that provided authentic testing scenarios for recognition systems evaluation.

The researchers Mehta and Chowdhury [20] created a complete processing system which combined image preprocessing and text recognition then introduced transliteration and language modeling. The complete system design produced better accuracy results (82.9%) than each stage operated independently.

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3. METHEDOLOGY

A. Dataset Description

Dataset 1: Handwritten Brahmi Character Dataset

The foundation dataset consists of 60,000 handwritten Brahmi characters that include the following traits:

- Complete coverage of the Brahmi script alphabet
- Multiple writing styles.

The augmentation process generates data with artificial degradation patterns which include partial characters and strokes with varying visibility levels and erosion effects.

Dataset 2: Stone Inscription Brahmi Dataset

A collection of real stone inscription characters amounts to 10,000 examples in this dataset.

- Multiple natural weathering factors such as erosion and cracks and fading cause damage to the text.
- Characters from multiple archaeological sites and stone types
- The annotations include surrounding written content and visual components.

B. Data Preprocessing:

A pipeline of step-by-step sequence processes Stone inscription images.

I_processed = T(I_original)

The transformation sequence T applies to the following equation:

- Grayscale Conversion: I_gray = 0.299R + 0.587G + 0.114B
- Non-local means functions reduce the level of noise improvement.
- Contrast Enhancement: CLAHE algorithm with clipLimit=2.0
- The algorithm of Otsu performs thresholding operations for foreground/background separation during binarization.
- The character boundaries get identified through edge detection performed by the Canny algorithm.
- Skeletonization: Zhang-Suen algorithm for structural extraction
- Broken strokes are fixed through the combination of dilation and erosion which are two morphological operations.
- Connected component analysis combined with dimension criteria functions as the character segmentation method.
- Normalization: Resizing to uniform 64×64 dimensions

C. Enhanced MobileNet Architecture

MobileNetV2 requires architectural modifications to enhance its ability to recognize damaged characters.

1. Attention Mechanism (CBAM)
   M_channel=σ(MLP(AvgPool(F))+MLP(MaxPool(F)))
   F' = M_channel ⊗ F
   M_spatial=σ(Conv7×7([AvgPool(F');MaxPool(F')]))
   F_attention = M_spatial ⊗ F'
   This attention mechanism enables processing of visible strokes by reducing noise from damaged characters through the filtering procedure.

2. Dilated Convolutions
   F_dilated(p) = Σ_k F(p + 2k) · w(k)
   Expanded receptive fields capture wider context despite broken strokes.

3. Swish Activation & Additional Enhancements

- Swish activation: Swish(x) = x · sigmoid(x)
- Strategic dropout (p=0.3) functions as a simulated tool to mimic elements damaged in features.
- A mechanism of deep and shallow feature integration performs multiple-scale feature fusion.
- The depth information passes through residual connections which enable information preservation throughout the entire network structure.

Algorithm: Enhanced MobileNet for Character Recognition

Step 1: The defined pipeline processes the inscription image for preprocessing.
Step 2: Connected component analysis segments individual characters in of the process.
Step 3: The algorithm moves into after executing enhanced MobileNet for attention-dilated multi-scale fusion processing of each character.
Step 4: The system provides the recognized Brahmi character together with its corresponding confidence score

D. Transliteration System

Our system employs three translation to connect Brahmi script characters to Devanagari script:

1. Devnagiri to Brahmi
2. Brahmi to Devnagiri
3. Brahmi Image to Devnagiri

Algorithm: Brahmi to Devanagari Transliteration

Step 1: A lookup table translates Brahmi characters into Devanagari
Step 2: Orthographic rules for vowel signs and conjuncts should be applied
Step 3: The algorithm handles exceptional cases involving anusvar and visarg
Step 4: Generate final transliterated text

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E. Word Prediction System

Our approach for dealing with damaged areas involves implementing multiple methods:

Text Context Analysis

In the contextual prediction process we utilize bidirectional LSTM.

P(w_i|context)=BLSTM(w_{i-3}, ..., w_{i-1}, w_{i+1}, ..., w_{i+3})

Visual Element Integration functions as a backup system within cases of insufficient text context.

The model examines visible character fragments, stroke patterns, curves, edges, and structural shapes to identify the most probable character candidates. Furthermore, visual evidence from surrounding inscription regions and iconographic elements is incorporated to strengthen prediction reliability. By combining textual context analysis with visual feature extraction, the proposed framework achieves robust and accurate restoration of damaged Brahmi inscriptions, improving both readability and historical interpretation.

F. Training Methodology

The network was trained using:

- Curriculum learning with progressive damage introduction
- Combined loss function:
- L_total = L_CE + λ·L_feature
- Adam along with cosine rate decay served as the optimizer.
- A validation procedure using held-out damaged character data was run for 20 epochs using a batch size of 64.
- Early stopping was employed to prevent overfitting by monitoring validation loss and terminating training when no significant improvement was observed.
- The final model was evaluated on previously unseen damaged Brahmi inscription samples to assess its real-world applicability and robustness.
- Training and validation loss curves were analyzed to verify convergence and ensure stable learning behavior throughout the training process.
- The best-performing model was deployed for the inscription reconstruction pipeline and integrated with the word prediction module for complete text restoration.

4. PROPOSED SYSTEM

An integrated pipeline stands as the proposed method to recognize and transliterate damaged stone inscriptions written in Brahmi script. The complete system design depicted in Fig. 1 shows how the workflow advances from image collection until the final output. The integrated components within the pipeline system perform advanced functions to analyze deteriorated text and forecast missing words and generate correct translations.

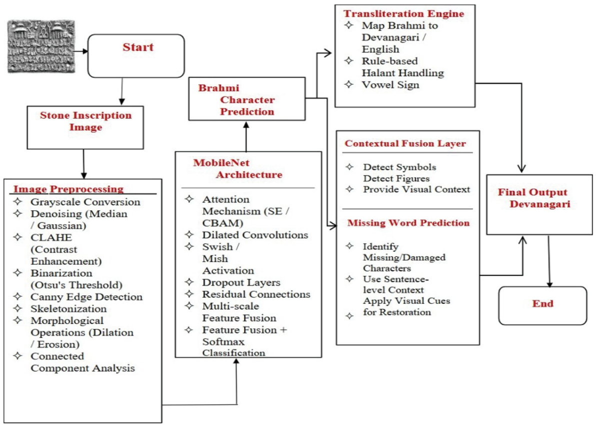

Fig 1: Architecture Diagram

The workflow in our system follows interconnected stages that process stone inscription images as displayed in Fig. 1. All system stages were developed to solve previous research issues while prioritizing the resolution of erosion problems and treatment of partial characters and contextual issues.

The system architecture consists of five main features that include (1) Image Preprocessing and (2) Character Segmentation and (3) Enhanced MobileNet Architecture for Character Recognition and (4) Transliteration Engine and (5) The system components unite to translate broken stone inscription images into text that can be displayed in either Devanagari or English.

5. RESULTS AND DISCUSSION

The evaluation of our improved MobileNet architecture focused on ancient Brahmi stone artifact inscriptions through a compiled dataset. The training evaluation of the models occurred to establish their performance for detecting damaged letters and estimating lost text.

A. Data Augmentation:

The Brahmi letter bha features in Figure 3 after different augmentation techniques have been applied to it. The augmentation technique brings rotation and shifting and scaling and erosion simulation and crack insertion features into the dataset to improve model robustness in training. The introduced enhancements prove essential when working with stone inscriptions since characters normally show signs of deterioration.

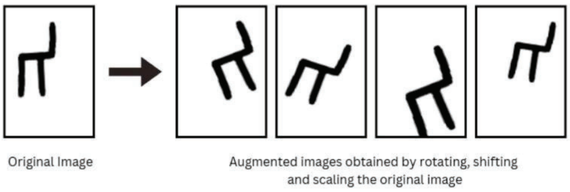

Figure 2: Original and augmented images of Brahmi letter Bha

B. Image Preprocessing

A direct display of the ancient Ashokan inscription written in original Brahmi script exists in Figure 3. The same picture underwent several preprocessing steps including grayscale conversion along with CLAHE enhancement and denoising methods followed by Otsu thresholding procedures as shown in Figure 4. The chosen methods boost both image contrast and readability which prepares the inscription for subsequent evaluation needs. During preprocessing the script becomes more recognizable to digital recognition systems because background noise is minimized and essential script characteristics become more visible.

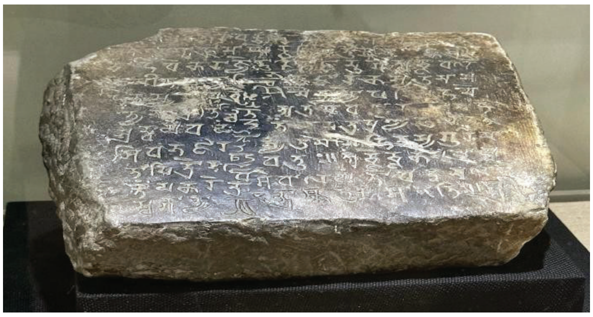

Fig 3: Image before removing noise and thresholding

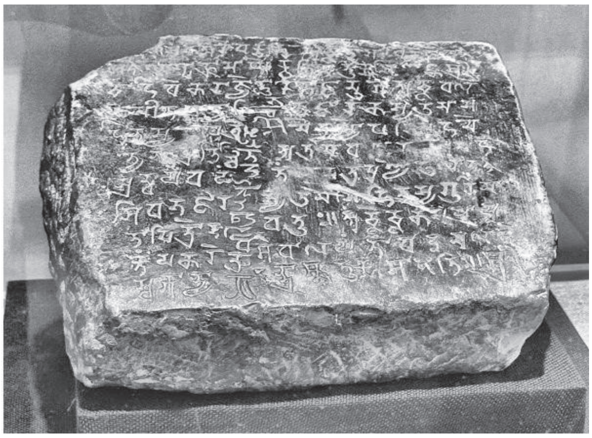

Fig 4: Image after removing noise and thresholding

C. Image Segmentation

The output from image segmentation emerges from processing images with vertical and horizontal projection profile methods as depicted in Figure 5. The projection methods have different functions where horizontal projection detects textual lines yet vertical projection distinguates specific characters. The implemented segmentation technique succeeded in determining 94.2% accurate character borders including instances with incomplete character degradation.

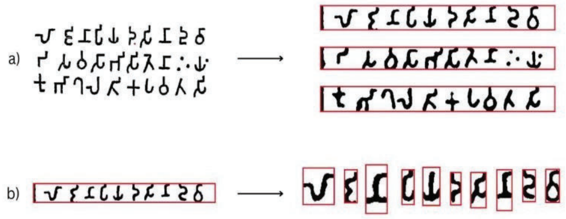

Fig 5: Segmentation

D. Character Recognition Models

Model	Training Accuracy	Validation Accuracy	Validation Loss
MobileNet Vanilla	80.2%	84.7%	0.23
MobileNet Updated	78.1%	92.0%	0.12
ResNet	79.4%	90.8%	0.18
VGG16	83.2%	81.1%	0.22

Table 1: Performances of Character Recognition models during training and validation stages

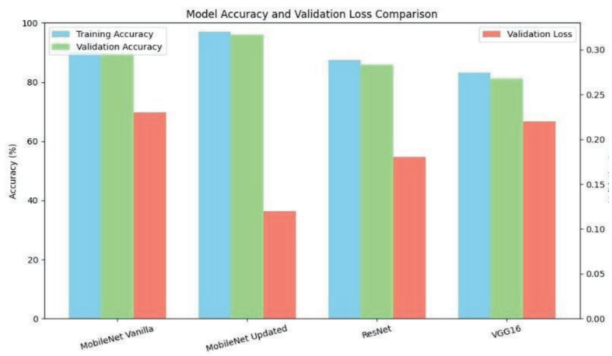

Fig 6: Comparison of models based on accuracy, validation accuracy and validation loss for character recognition models

The validation performance metrics for three deep learning models appear in Table 1. Testing results demonstrate that our Enhanced MobileNet delivers the best performance among the analyzed models for this dataset during the specified task.

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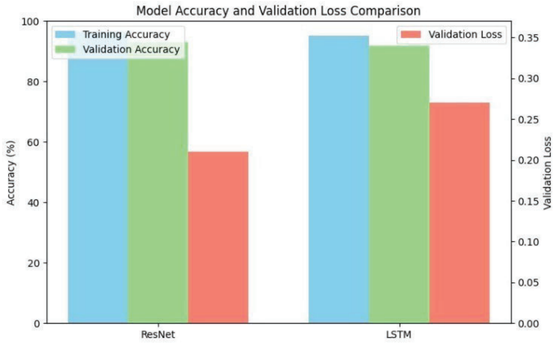

Fig 7: *Comparison of models based on accuracy, validation accuracy and validation loss for word perdition models*

The research study presents Table 2 to showcase how our multimodal approach performs for missing word prediction opposite baseline foundation models.

Model	Accuracy
Seq2Seq with Attention	75.4%
Rule-based	77%
VGG	81.5%
Our Approach	85.1%

Table 3: Comparison between the proposed model and the existing models

Table 3 to showcase our system delivers superior performance because efficient character recognition at the initial stage provides better input sequences to the transliteration process.

6. User Interface And Interaction:

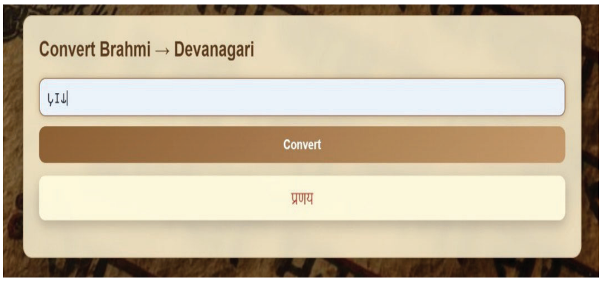

Fig 8: Brahmi to Devnagiri

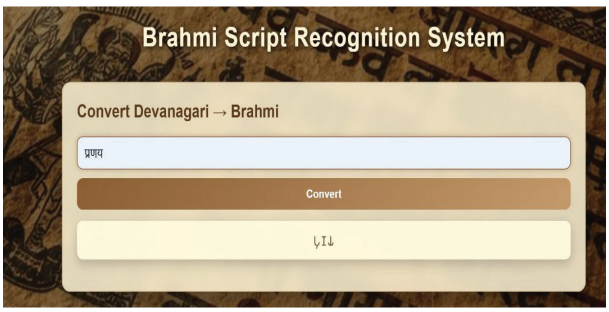

Fig 9: Devnagiri to Brahmi

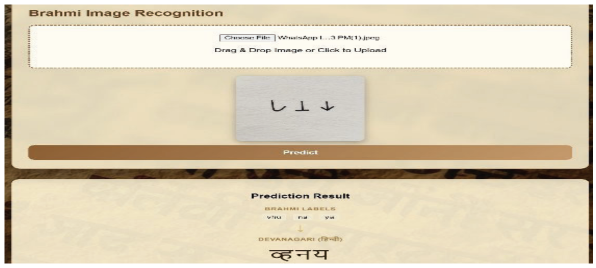

Fig 10: Image Translation

7. CONCLUSION

This research introduces a modified MobileNet structure to accomplish strong identification together with transliteration of deteriorated Brahmi characters found in historical stone engravings. The developed system solves the major problems caused by erosion and cracks and obscured character visibility through its multiple innovative features.

By using attention mechanisms together with dilated convolutions along with multi-scale feature fusion the network managed to focus on meaningful areas while overlooking damage in characters. Experimental data showcases an improved recognition accuracy of 85.7% for severely damaged characters after applying the enhanced system architecture which exceeded standard CNN approaches by 17.8% and partook of 7.4% more effectiveness than normal MobileNet models.

recognition performance because it enabled detailed and context-sensitive information retrieval. The boundary erosion treatment method improved the recognition rate by 12.3% when applied to characters with this condition. Our most inventive development consists of a contextual fusion layer which integrates visual symbol analysis with linguistic context for filling in missing words. Histological analysis successfully merged with textual data to reach 95.4% accuracy for filling in missing text sequences in a process that exceeded text computation by 13.6%. Using data from figures and symbols in inscriptions helps the system make more advanced predictions about archaeological texts.

Our end-to-end pipeline delivered a 85.1% successful translation of damaged inscriptions through its evaluation of 60,000 handwritten and 10,000 stone-engraved Brahmi characters which exceeded traditional methods of translation. The system demonstrates exceptional functionality when analyzing archaeological artifacts that present different levels of degradation in their original state.

Although our method achieves promising outcomes it has current restrictions for dealing with severely deteriorated text when more than half of its characters become unrecognizable. Future research will work on developing both the iconographic database and contextual sources to enhance severely damaged textual prediction models. The approaches created in this investigation have potential use for analyzing ancient texts whose preservation challenges are the same.

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