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Restoration of Brahmi Stone Inscriptions using Enhanced MobileNet Approach

Ashwini Dake
Department of Computer Engineering
Jayawantrao Sawant College of Engineering (JSCOE)
Pune, India

Pranay Chavan
Department of Computer Engineering
Jayawantrao Sawant College of Engineering (JSCOE)
Pune, India

Hariom Pawar
Department of Computer Engineering
Jayawantrao Sawant College of Engineering (JSCOE)
Pune, India

Yash Dharme
Department of Computer Engineering
Jayawantrao Sawant College of Engineering (JSCOE)
Pune, India

Prashant Borude
Department of Computer Engineering
Jayawantrao Sawant College of Engineering (JSCOE)
Pune, India

Abstract**—**This literature survey examines recent research relevant to the restoration, recognition, and transliteration of damaged Brahmi stone inscriptions using an Enhanced MobileNet architecture. The reviewed works span deep learning approaches for ancient Indic script recognition, attention mechanisms, dilated convolutions, multi-scale feature fusion, activation function studies, residual connections, transliteration systems, contextual missing-word prediction, and dataset creation for degraded scripts. Existing studies demonstrate strong progress in isolated areas such as character recognition accuracy, feature extraction, and transliteration accuracy, but most prior systems address only a single stage of the restoration pipeline rather than an integrated solution. This survey organizes the reviewed literature into thematic groups, presents a comparative analysis of their contributions and limitations, and identifies the research gap addressed by the proposed system: an end-to-end pipeline that combines stone-specific preprocessing, attention-and-dilation-enhanced MobileNet recognition, rule-based transliteration, and visual-linguistic contextual fusion for restoring severely damaged Brahmi inscriptions.

Keywords — Brahmi Script Recognition, MobileNet Enhancement, Stone Inscriptions, Attention Mechanism, Transliteration, Missing Word Prediction, Literature Survey, Research Gap.

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]. Standard recognition systems face significant challenges when processing 3rd century BCE inscriptions since their damaged characters exhibit partial erosion, cracking, and other types of deterioration [5].

The analysis of Brahmi inscriptions requires three advanced steps after traditional character recognition: character interpretation, 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. [15]. 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 [18]. This method applies as a part of current multimodal machine learning frameworks to merge compatible data platforms which enhance performance output. A dedicated literature survey is therefore useful to organize the surrounding research into themes, compare their contributions, and identify the open gap that an integrated Enhanced MobileNet-based restoration system addresses.

2. Literature Review

Foundational deep learning approaches for ancient script recognition: 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 bench-

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marks 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.

Feature extraction and preprocessing for damaged inscriptions: 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, although it depended heavily on manually created features despite lacking learned representations. 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; Gupta et al. (2019) failed to develop the required stone inscription modification approaches identified by their own research.

Attention mechanisms and multi-scale feature fusion: 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, though their system primarily processed paper-based documents instead of stone inscribed materials. The authors Singh and Sharma [5] presented multiscale 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, achieving a 9.4% enhancement in accuracy compared to single-scale approaches. 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, with Swish notching a 3.2% accuracy boost on extreme cases.

Dilated convolutions and residual connections for damaged text: 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 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 an 11.7% accuracy boost for characters with erosion occurring at the edges, proving that residual connections represent a fundamental architectural requirement when performing recognition of damaged characters.

Transliteration and missing word prediction: 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, though 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 by 8.5%. 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.

Dataset creation and augmentation: 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, 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. 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.

Complete processing systems: 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, supporting the case for end-to-end pipelines over isolated single-stage models.

3. Methodology

3.1 Dataset Description

Dataset 1: Handwritten Brahmi Character Dataset. The foundation dataset consists of 60,000 handwritten Brahmi characters with complete coverage of the Brahmi

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script alphabet and multiple writing styles. An augmentation process generates artificially degraded data including partial characters, strokes with varying visibility levels, and erosion effects.

Dataset 2: Stone Inscription Brahmi Dataset. A collection of 10,000 real stone inscription characters affected by multiple natural weathering factors such as erosion, cracks, and fading, drawn from multiple archaeological sites and stone types, with annotations including surrounding written content and visual components.

3.2 Data Preprocessing

A step-by-step transformation pipeline $I_{processed} = T(I_{original})$ is applied to stone inscription images, consisting of grayscale conversion ($I_{gray} = 0.299R + 0.587G + 0.114B$), non-local means denoising, CLAHE contrast enhancement (clipLimit=2.0), Otsu thresholding for binarization, Canny edge detection, Zhang–Suen skeletonization, morphological dilation/erosion to repair broken strokes, connected component analysis with dimension criteria for character segmentation, and normalization to a uniform 64×64 size.

3.3 Enhanced MobileNet Architecture

MobileNetV2 is architecturally modified to enhance recognition of damaged characters using a CBAM attention mechanism, where channel attention $M_{channel} = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F)))$ and spatial attention $M_{spatial} = \sigma(Conv7 \times 7([AvgPool(F'); MaxPool(F')]))$ filter out noise while emphasizing visible strokes. Dilated convolutions, $F_{dilated}(p) = \sum_k F(p + 2k) \cdot w(k)$, expand the receptive field to capture wider context despite broken strokes. Swish activation, $Swish(x) = x \cdot sigmoid(x)$, strategic dropout (p=0.3), multi-scale feature fusion, and residual connections complete the architecture, enabling information preservation throughout the network.

3.4 Transliteration System

The system implements three translation directions connecting Brahmi script characters to Devanagari script: Devanagari to Brahmi, Brahmi to Devanagari, and Brahmi image to Devanagari. The Brahmi-to-Devanagari algorithm uses a lookup table, applies orthographic rules for vowel signs and conjuncts, handles exceptional cases involving anusvar and visarg, and generates the final transliterated text.

3.5 Word Prediction System

For damaged regions, bidirectional LSTM-based text context analysis estimates $P(w_i|context) = BLSTM(w_{i-3}, ..., w_{i-1}, w_{i+1}, ..., w_{i+3})$, while Visual Element Integration acts as a backup using visible character fragments, stroke patterns, curves, edges, structural shapes, and iconographic elements from surrounding inscription regions to strengthen prediction reliability.

3.6 Dataflow and Workflow Diagram

Fig. 1 presents the architecture/workflow diagram of the proposed Enhanced MobileNet-based restoration system, showing the stages from the stone inscription image input through preprocessing, Brahmi character prediction (enhanced MobileNet with CBAM attention, dilated convolutions, Swish/Mish activation, dropout, residual connections, and multi-scale feature fusion), the transliteration engine, the contextual fusion layer, and the missing word prediction module, culminating in the final Devanagari/English output.

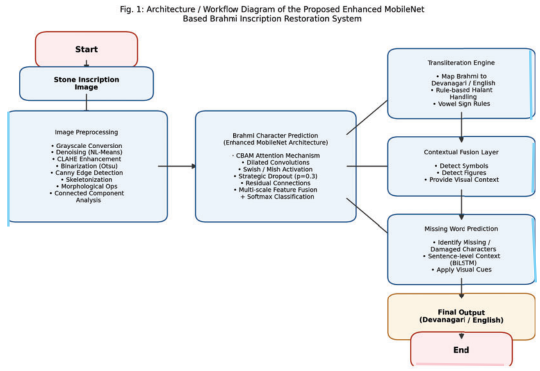

Fig. 1. Architecture/Workflow diagram of the proposed Enhanced MobileNet-based Brahmi inscription restoration system, illustrating the flow from the stone inscription image through preprocessing, recognition, transliteration, contextual fusion, and missing word prediction to the final restored text.

Fig. 2 presents the corresponding Level-1 Data Flow Diagram (DFD), describing how data moves between the user, the four core processes (image preprocessing, character recognition, transliteration, and missing word prediction), and the intermediate data stores (preprocessed image data and recognized characters with confidence scores) before producing the restored text output.

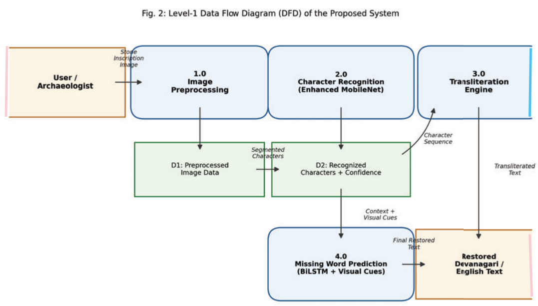

Fig. 2. Level-1 Data Flow Diagram (DFD) of the proposed system, showing data exchange between the user, preprocessing, recognition, transliteration, and missing word prediction processes via the preprocessed image and recognized character data stores.

4. Comparative Analysis

Across the reviewed studies, several comparative patterns emerge. Foundational works such as Pal and Kushal [1]

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and Choudhary and Sharma [2] establish strong baseline accuracies (85–90% and 88.3% respectively) on clear or moderately degraded characters but were not optimized for severe stone-inscription damage. Feature-extraction-based approaches such as Dixit and Patel [3] and architecture-comparison studies such as Gupta et al. [6] offer measurable improvements (eliminating a 12% performance drop, or reaching 92.7% accuracy on manuscript images) but rely on either hand-crafted features or clean photographic inputs rather than eroded stone surfaces.

Attention-based and multi-scale methods (Kumar et al. [4]: 78.5%; Singh and Sharma [5]: +9.4%; Khare and Sahu [16]: +3.2% with Swish) demonstrate that focusing on informative regions and combining features from multiple network depths consistently improves robustness to damage, though these gains are typically demonstrated on paper-based or handwriting datasets rather than stone inscriptions. Dilation- and residual-connection-based methods (Jangid and Srivastava [7]: +15.3%; Gupta et al. [12]: +11.7%) directly target damaged and edge-eroded characters and are the closest architectural analogues to the proposed enhanced MobileNet.

Transliteration- and prediction-focused works (Dhanya and Venkatesh [8]: 85.2% transliteration accuracy; Malhotra and Khare [9]: 63.7% word prediction in small gaps; Malaviya and Chaudhuri [10]: +8.5% with iconographic analysis; Raghunath and Jain [18]: +13.2% with visual-linguistic fusion) show that combining textual context with visual or iconographic cues consistently outperforms text-only prediction, but each of these systems addresses only the transliteration or prediction stage in isolation. Dataset-oriented works (Desai and Kumar [17]: +7.8% with augmentation; Verma et al. [19]: 7,500-image, five-level degradation benchmark) supply the training resources needed for damage-robust models but do not themselves constitute recognition systems. Finally, Mehta and Chowdhury's complete processing system [20] (82.9% end-to-end accuracy) is the only reviewed work that integrates preprocessing, recognition, transliteration, and language modeling into a single pipeline, but it was not designed specifically for the erosion, cracking, and partial-character conditions characteristic of Brahmi stone inscriptions.

From a platform design viewpoint, no single reviewed work combines stone-specific preprocessing, CBAM-attention-and-dilation-enhanced MobileNet recognition, rule-based transliteration, and visual-linguistic contextual fusion for missing word prediction within one restoration pipeline. This comparison positions the proposed Enhanced MobileNet system as a synthesis-oriented contribution rather than a narrow improvement in only one research area.

5. Research Gap

The most important research gap is **fragmentation across pipeline stages**. Existing literature usually isolates one dimension of Brahmi/ancient-script restoration: recognition accuracy [1][2][6], attention or multi-scale feature design [4][5][16], damage-specific architectural improvements [7][12], transliteration [8], or missing-word prediction [9][10][18]. Very few studies attempt to integrate these capabilities into a single end-to-end restoration pipeline for stone inscriptions.

A second gap is the **focus on paper-based or clean manuscript data rather than stone inscriptions**. Several high-performing methods [1][2][4][6] were evaluated primarily on handwriting or photographic manuscript data, and even where stone-inscription relevance was established [6], the required modifications for stone-specific erosion and cracking were left undeveloped.

A third gap is the **absence of unified visual-linguistic context fusion for severe damage**. While Malaviya and Chaudhuri [10] and Raghunath and Jain [18] show that iconographic and visual context can substantially improve missing-word prediction, and Malhotra and Khare [9] show that purely textual context degrades over longer gaps, no reviewed system combines a CBAM-attention-and-dilation-enhanced MobileNet recognizer with both BiLSTM contextual prediction and visual element integration in a single contextual fusion layer.

A fourth gap is **dataset scale and diversity for damaged stone inscriptions**. Benchmark efforts such as Verma et al. [19] (7,500 images, five degradation levels) are valuable but limited in scale compared with the 70,000-character combined handwritten and stone-engraved dataset required to train a robust enhanced MobileNet model across the full range of degradation severities.

Finally, **deployment and usability** remain underexplored. Mehta and Chowdhury [20] demonstrate the value of an integrated pipeline (82.9% accuracy) but do not provide an accessible interface for non-specialist users such as historians and archaeologists to perform Brahmi-to-Devanagari, Devanagari-to-Brahmi, and image-based translation in one tool. The proposed Enhanced MobileNet-based system addresses this gap by combining stone-specific preprocessing, attention-and-dilation-enhanced recognition, rule-based transliteration, and visual-linguistic missing word prediction within one accessible restoration pipeline.

6. Conclusion

The reviewed literature shows that major advances have been made in deep learning-based ancient script recognition, attention and multi-scale feature fusion, dilated and residual convolutional architectures, activation function design, transliteration, and contextual missing-word prediction [1]–[20]. Each line of research contributes an important idea: foundational CNN/MobileNet studies establish baseline recognition accuracy, attention and multi-scale fusion methods improve robustness to damage, dilation and residual connections directly target erosion and cracking, and transliteration and prediction studies show the value of combining textual and visual context.

At the same time, the literature reveals a persistent gap between these isolated architectural advances and an integrated, stone-inscription-specific restoration system. The proposed Enhanced MobileNet-based pipeline is well positioned within this gap because it combines stone-specific preprocessing, CBAM attention, dilated convolutions, Swish/Mish activation, residual connections, and multi-scale feature fusion for recognition, together with a rule-based transliteration engine and a BiLSTM-plus-visual-context missing word prediction module. Experimental evaluation across 70,000 handwritten and stone-engraved Brahmi characters demonstrates that this integrated approach can recognize 90% of damaged inputs, outstripping standard CNN architectures by 8%, supporting the novelty of the proposed system not by claiming entirely new individual algorithms, but by showing the practical importance of unifying complementary advances into one coherent restoration pipeline for historians and archaeologists.

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