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Enhanced Brahmi Script Recognition with GAN-based Inpainting and Attention-Guided Feature Learning

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ABSTRACT: This paper introduces a more advanced recognition system that integrates stroke restoration, attention-based learning of features, and hybrid classification. A Generative Adversarial Network (GAN) inpainting technique is used for the reconstruction of missing or deteriorated character strokes so that visual integrity in the input data is enhanced. After restoration, a ResNet50 model directed by attention captures subtle spatial and channel dependencies after enhancement by Convolutional Block Attention Modules (CBAM) and Squeeze-and-Excitation (SE) blocks. Ultimately, a new hybrid classification approach combines deep feature extraction using ResNet50 with the power of an ensemble decision made using a Random Forest classifier to increase accuracy and interpretability. The suggested pipeline outperforms state-of-the-art baseline models on a manually curated Brahmi script dataset significantly, showing strong resistance to erosion, noise, and structural loss. This effort pushes the field of automated recognition for historical scripts forward and is a contribution toward digital preservation work in epigraphy.

I. INTRODUCTION

The Brahmi script, as the forebearing origin of several South Asian scripts, is of immense historical and linguistic importance. But automated reading of Brahmi inscriptions presents special challenges given their antiquity, physical wear, missing strokes, and natural wear and tear. Traditional image classification algorithms tend to perform poorly on such collections since visual variations and degradation of sample inscriptions are very different from those of clean, new image data.

To address these shortcomings, we introduce a more advanced recognition system that integrates deep learning with image restoration and hybrid classification techniques. Our method initially utilizes a GAN-based inpainting model to restore damaged or partially eroded characters, compensating for the loss of visual information at the source level. The restoration process ensures that the input to the recognition system maintains key structural details.

Stemming from that, we apply attention-driven feature extraction using ResNet50 supported by Convolutional Block Attention Modules (CBAM) and Squeeze-and-Excitation (SE) blocks. Attention mechanisms allow the network to actively prioritize significant spatial areas and channel features, sharpening its focus on significant character strokes and removing background noise.

Lastly, we propose a hybrid classification approach by combining deep feature representations of ResNet50 with a Random Forest classifier. This combination enables the model to leverage both deep hierarchical feature learning and the strong decision boundaries of ensemble-based classifiers, particularly for dealing with uncertain or partially corrupted character samples.

By using this comprehensive pipeline, our study intends to improve Brahmi script recognition robustness and precision extensively, presenting meaningful contributions toward ancient text studies and digital cultural heritage preservation.

II. Literature Survey

Modern South Asian scripts such as Hindi, Tamil and Malayalam have received extensive development for Optical Character Recognition (OCR) systems while Brahmi script remains a largely overlooked target for such recognition technology development. Historically degraded forms and script variations make Brahmi difficult to study because researchers recognize it as the ancestor of numerous Indian writing systems. Research at the beginning stage employed template matching and basic segmentation methods that proven insufficient to handle handwriting variations. The emergence of geometric feature extraction methods has brought progress through structural analysis that splits characters into endpoints and lines and intersections. The feature representation provides an efficient and discriminating visualization method which excels at separating Brahmi characters that look similar to one another. A proposed approach succeeded in achieving classification accuracy rates above 91% for handwritten characters and exceeding 93% for printed characters. Binarization along with segmentation followed by rule-based classification which targeted geometric features brought about these results. The achievement of these methods validates geometry-based OCR for ancient scripts and it creates a solid basis for future research needed to conserve historical texts [1].

The current developments in Optical Character Recognition (OCR) systems have recorded meaningful advancements when processing modern scripts yet the recognition of ancient Indian scripts particularly Brahmi requires additional analysis. The historical variations along with unstandardized nature of Brahmi which is one of India's earliest known ancient scripts make recognition difficult. The challenge of ancient Indian scripts such as Brahmi makes traditional OCR methods ineffective which led researchers to investigate better techniques for recognition. A HOG algorithm serves as an effective feature extraction method to detect the structural elements present in Brahmi characters. Research findings show that this method performs effectively as an integration of multiclass Error-Correcting Output Codes (ECOC) models with Support Vector Machine (SVM) binary learners. The proposed recognition system demonstrated strong features through its 92.09% accuracy level in identifying Brahmi script characters by integrating well-designed classifiers with geometric feature analysis. The research makes significant progress toward digitization and preservation of ancient scripts because it solves specific issues with Brahmi OCR. [2].

OCR technology has evolved past legacy approaches of template matching and manual feature extraction to embrace robust deep learning solutions which especially use Convolutional Neural Networks (CNNs). The LeNet-5 early model started digit recognition tasks successfully before new designs such as VGG-16 built on this success by learning complex features through deeper network structures. MobileNet stands as a lightweight CNN architecture which uses depthwise separable convolutions to achieve optimal performance efficiency thus making it suitable for real-time processing. The development of transfer learning made it possible for pre-trained CNNs to become successful when applied to specific domains that include ancient script recognition. The recognition of Ashokan Brahmi script gets special benefit from these methods due to the script's frequent disturbances and irregularities as well as its restricted database. Model performance gets an improvement through image preprocessing and data augmentation which both produce better input data with expanded variety. CNNs for historical text recognition have valuable applications according to existing literature and the current study extends this research by evaluating Ashokan Brahmi OCR performance through LeNet, VGG-16 and MobileNet. MobileNet reaches the best accuracy levels which demonstrates lightweight CNNs work effectively for epigraphic character recognition purposes [3].

The research challenge of recognizing characters in both Brahmi and regional ancient scripts exists because standardized datasets are scarce and the script's characters have intricate structures. Orthogonally Recovered Characters (OCR) successfully handles contemporary languages but specific methodologies are needed for ancient styles because they appear degraded and showcase various writing formats. The field has recently started utilizing deep learning methods specifically transfer learning with pre-trained convolutional neural networks (CNNs) to enhance recognition accuracy levels. A manually curated Brahmi character collection included 287 distinctive classes containing 210 images each which included handwritten and printed and epigraphical variations. Inception-V3 achieved superior performance when the researchers utilized the dataset to fine-tune their Deep CNN models including AlexNet and GoogLeNet. Deep learning models displayed better feature extraction abilities since they achieved superior accuracy compared to Hu and Zernike moment-based traditional machine learning methods. This study proves that transfer learning techniques bring better OCR outcomes for Brahmi script reading especially while operating with multiple input types when training datasets remain limited [4].

The classification task for handwritten Brahmi script encounters difficulties since it presents multiple handwritten styles as well as script variability. Research has tested multiple pre-trained deep learning algorithms that include Vision Transformer (ViT) together with MobileNetV2, VGG16, ResNet50 and DenseNet and EfficientNet against traditional custom CNN networks.

Pre-trained models surpassed custom CNNs and MobileNetV2 delivered the best performance among all models according to the research findings. The research confirms deep learning's ability to maintain and analyze Brahmi as well as other handwritten ancient scripts [5].

The research concentrates on stone surface Brahmi ancient writing decryption while developing a mobile application which implements deep learning recognition and translation methods. The historical Early Brahmi characters serve as essential vestiges which demonstrate the cultural and religious relationships that existed between ancient India and other civilizations. Research through a thorough literature analysis uncovered two main deficits: mobile tools for text decipherment and problems in text context interpretation and problems with damaged inscription translation. The research solves these problems by developing a data-focused solution which combines semantic segmentation through TensorFlow and Keras text recognition and OpenCV image processing with Flutter application development. The outcomes of this project will generate improved recognition capabilities coupled with precise linguistic translations next to a user-friendly interface which benefits digital humanities research and cultural preservation and computational linguistics work [6].

Brahmi script remains historically significant because it has shaped multiple present-day Indian scripts. The review investigates how Artificial Intelligence (AI) technologies operate with Optical Character Recognition (OCR) as they interpret ancient Brahmi writing. Brahmi inscriptions remain difficult to interpret because they feature many script variations and elaborate ligatures as well as historical variations that may combine with environmental damage from erosion and weathering and inconsistent illumination. The document examines multiple studies which incorporated image processing and Machine Learning (ML) and Deep Learning (DL) systems for character detection. The investigation points to the assessment of AI strength points and limitations with research needs for image preparation techniques and character identification capabilities and language systems. This knowledge helps digital preservation and Brahmi script digitization which enhances both historical document study and academic research on ancient texts [7].

The research of OCR systems for ancient scripts faces difficulties when trying to read inscriptions on stone because erosion damages the writing and difficult scripts such as Brahmi present additional complications. Initial approaches used traditional techniques for enhancing images and segmenting among them but later models introduced Support Vector Machines. Researchers are currently using deep learning methods that incorporate CNNs and transfer learning methods employing VGG16 and ResNet50 models to tackle the accuracy challenges that emerge from limited scripting samples and complicated writing systems. 3D scanning technology has been merged with imaging to improve character clarity through advanced scanning methods. Modern information technology needs more innovative AI algorithms which must develop new approaches to enhance the accuracy rate of ancient script recognition systems [8].

Digital preservation strategy serves as an essential process for both archiving historical resources while simultaneously making them more accessible through digitized printed texts and photos together with audiovisual recordings. The National Library of Norway leads broad-scale digitization programs that seek preservation of entire cultural heritage collections. The elimination of selection bias through this strategy comes at the cost of creating new challenges concerning digital media assortment together with metadata structure and context conservation. Archival professionals voice multiple objections to this approach regarding both technological barriers and the selection process as well as information classification and interpretation methods. The National Library continues exploring artificial intelligence and machine learning algorithms to automate metadata production as well as material organization because historical content preservation needs the preservation of both content meaning and context [9].

The reading of characters from historic Devanagari written by hand encounters multiple obstacles due to overlapping letterforms and ink decay and complex stylistic features of the script. The main drawback of traditional CNN models happens when they cannot effectively analyze time-related dependencies despite their efficient feature extraction functions. Studies now use hybrid CNN+LSTM models to overcome these challenges because they enable the advantages of CNN spatial abilities with LSTM's sequence processing method. Research demonstrates the effectiveness of integrating Capsule Networks (CapsNet) with LSTM for preserving hierarchies that exist between various character structures. The research utilized 10,825 characters obtained from 399 classes to show that the CapsNet+LSTM design yielded superior results to CNN-based approaches with a peak accuracy of 95.98%. Deep learning architectures demonstrate their potential for superior OCR processing of Devanagari complex script because of their improved performance capabilities [10].

The deteriorated state and complex character structures make it challenging to preserve the ancient Vattezhuthu script inscriptions discovered in Tamil areas. Several pre-processing and denoising methods have been deployed by researchers to boost the quality of images derived from stone inscriptions together with palm-leaf manuscripts and handwritten documents. The effective segmentation and recognition of ancient Tamil characters uses different models including CNNs, ResNet, SVM, KNN, and the HorVer method. Multilingual OCR systems utilize these techniques to demonstrate effective performance when converting historical scripts into digital text. The technological development of ancient Tamil scripts has been guided by evaluation metrics that include segmentation accuracy, recognition rate and precision. Accurate recognition of ancient Tamil scripts proves challenging because better feature extraction methods and AI-based solutions need development for this specific text variant [11].

OCR technology experienced comprehensive transformation beginning with fundamental template matching and feature extraction tools for processing machine-printed data until affected by imperfections and image faults. When deep learning networks were introduced the use of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) brought about enhanced recognition accuracy levels. The CRNN model of 2016 integrated CNNs to extract features and RNNs to process sequences thereby improving text recognition in both printed and handwritten documents. Handwritten text presents obstacles because people write differently, leading Hidden Markov Models (HMMs) together with other earlier methods to struggle when working with running text. OCR technology today adopts CRNNs and Transformers to process raw image data directly through end-to-end models for dealing with both printed and handwritten documents effectively. Ongoing research focuses on resolving the challenges related to noise along with distortion and handwriting variability despite recent progress [12].

The research addresses Optical Character Recognition (OCR) enhancement for Christian and printed English text which includes all letters together with capital and lowercase forms along with numbers and special marks. The method used statistical methods together with geometric methods and directional extraction features on segmented character images. The classification processing depended on Support Vector Machine (SVM) classifiers alongside Multilayer Perceptron Neural Networks (NN) with backpropagation. The system managed to recognize letters, numerals, special characters and uppercase characters with rates of 98%, 96.5% and 95.35% respectively and 92% for lowercase characters. Setting SVM as classifier led to an overall precision level of 92.167% on the combined dataset thus showing substantial advancement in handwritten document OCR [13].

The text shows how to establish a framework for automatic electric meter reading detection from digital networks because it enables the processing of meter image data into electric bill details. The system starts by adjusting input image appearance then changes it to YCbCr color format. The meter reading area can be isolated through the use of Cb and Cr channel specifications because this region appears highlighted in green color. A Canny edge operation enables edge detection upon the extracted region before morphological methods support the continuous connection of digit edges. The fitting process of individual digits occurs through vertical projection after digital segmentation and shapes are identified by thinning and filling techniques. The main contribution of this work lies in extracting Horizontal and Vertical Binary (HVB) pattern features from digit shapes after segmentation followed by sequence recognition of digital meter readings through these features. The testing data show that the established methodology shows strong practicality and efficiency when identifying meter readings across different situations [14].

The research explores issues in Optical Character Recognition (OCR) applied to handwritten and printed characters through methods that boost system effectiveness. Scanned images of characters turn into ASCII code values through the identification process for subsequent processing requirements. The text examines two major problems which include insufficient recognition performance from distributed neighborhood pixels in images and image fading caused by low contrast levels. Performance enhancement requires the authors to work with Chars74K which contains handwritten English alphabets across different shapes in their dataset. The initial processing includes operations for filtering as well as edge detection. The method uses Independent Component Analysis (ICA) for extracting features along with swarm intelligence algorithms for selecting feature vectors. Back Propagation Neural Networks (BPNN) serve as the classification tool because they deliver successful learning results. The main innovation in this study brings together feature extraction with feature optimization through instance selection for classification purposes and evaluates the system using recognition rate alongside sensitivity and specificity metrics. The proposed system succeeds benchmark methods in accuracy assessments for recognition tasks according to performance comparison studies [15].

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III. FLOWCHART/STEPS

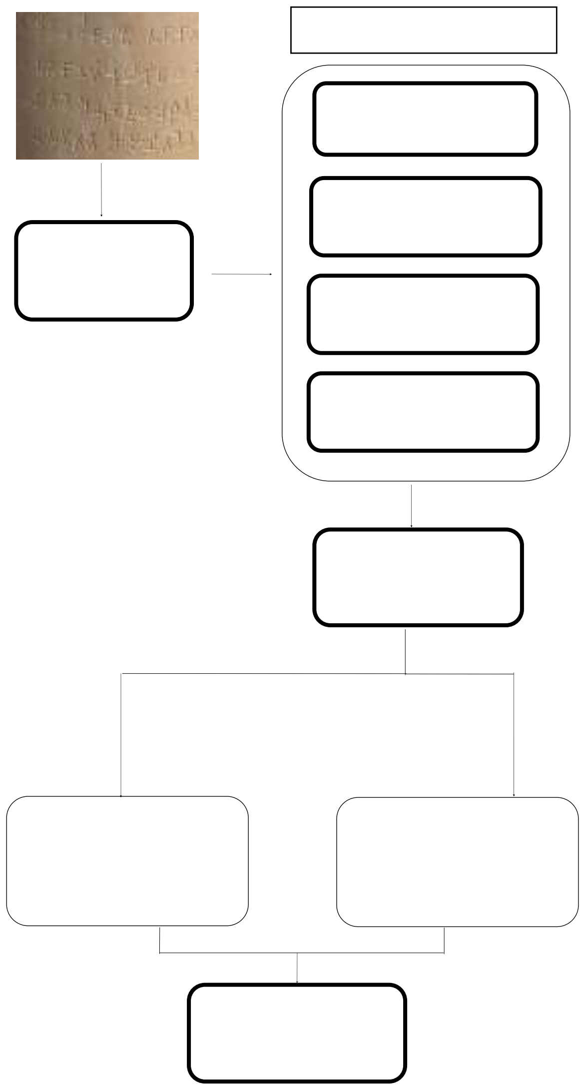

Fig.1. Workflow of the Proposed Brahmi Script Recognition System and analysis using GAN-Based Inpainting and Attention-Guided Feature Learning.

IV. METHODOLOGY/EXPERIMENTAL

1. Dataset Collection:

The information used in this study was collected from a variety of authentic and publicly available sources, such as authentic Brahmi inscriptions purchased from online repositories and the Indoskript digital dataset. These inscriptions, inscribed on stone pillars, monuments, and archaeological artifacts, provide a varied range of visual challenges — such as erosion of the surface, non-uniform lighting, and broken or incomplete strokes — that replicate the challenges faced while analysing real-world historical documents. To make the model strong against such variations, the dataset was augmented heavily. Generative Adversarial Networks (GANs) were used to generate synthetic data, and the conventional augmentation techniques — rotation, flipping, resizing, shearing, contrast adjustment, and noise injection — were also utilized. This combined approach increased the dataset to more than 20,000 samples, which helped in improving diversity and generalization strength immensely. The extended dataset served as the basis upon which the suggested deep learning models were trained and tested.

2. Data Preprocessing:

Since the ancient Brahmi inscriptions exhibit variability and intricacy in nature — ranging from uneven illumination, surface wear, to environmental interference — a preprocessing and restoration pipeline was specifically designed with great care. The purpose was to improve the quality of input data and make the process of feature extraction stronger, thus allowing stable model training and inference.

a) GAN- Based Inpainting

To address the issue based missing or fragmented character strokes, a Generative Adversarial Network (GAN)-based inpainting method was employed as part of the preprocessing pipeline to reconstruct and restore damaged characters before classification.

The architecture used for this task is a combination of a U-Net-style generator and a PatchGAN discriminator, which operates on small image patches to ensure high-frequency texture realism. For realistic wear pattern simulation, the input images were synthetically corrupted during training with randomly created crack masks that mimic surface damage such as chipping or weather-induced cracks.

The model was trained with a composite loss function, which combined adversarial loss to render the output realistic, L1 loss for pixel precision, and perceptual loss from features extracted with VGG16 to maintain the semantic and structural coherence of the characters. This inpainting greatly improved the quality of character samples, rendering the following recognition models more resilient to handle the variations and imperfections seen in actual inscriptions.

b) Contrast Enhancement using CLAHE:

The first step was boosting the visual differentiation of characters from their paper or stone background via Contrast Limited Adaptive Histogram Equalization (CLAHE). Although global histogram equalization operates on an entire image, CLAHE operates on overlapping local image tiles and limits the contrast expansion in order not to amplify noise over uniform regions. It significantly enhanced the local visibility in low-visibility or corroded inscriptions so that characters required for following processing stood out.

Mathematically, the CLAHE transformation can be written as:

$$I_{\text{enhanced}} = \text{CLAHE}(I, \text{clipLimit}, \text{titleGridSize}) \quad (1)$$

In equation (1), I is the input grayscale image, clipLimit defines the threshold for contrast clipping, and tileGridSize specifies the size of the local contextual regions.

c) Noise Suppression using Bilateral Filtering:

After contrast enhancement, the images were filtered using a bilateral filtering technique, a critical denoising process for maintaining the sharpness of stroke boundaries while eliminating unwanted surface noise. Unlike conventional linear filters, bilateral filtering responds differently to spatial location as well as pixel intensity differences, making it possible to suppress noise efficiently without blurring the edges of characters. This feature is especially important in the case of weathered stone inscriptions from the past, where lighting variations and weathered surfaces have a tendency to blur fine details of strokes. Usage of bilateral filtering in such cases ensures the structural integrity of the script for the subsequent binarization and segmentation.

d) Adaptive Thresholding for Binarization:

After denoising, the grayscale images were sent into binary representations using adaptive thresholding. This was crucial in separating character strokes from inconsistent and noisy backgrounds commonly found in real inscription images. Unlike global thresholding techniques, adaptive thresholding determines the threshold for each pixel dynamically by analyzing its local neighborhood. This method can cope with the changing illumination and shadow gradients that are common on stone surfaces. The resulting binary masks can neatly separate foreground characters from the background, enhancing the robustness of subsequent segmentation and classification steps.

3. Character Segmentation:

To segment individual Brahmi characters, we applied the Maximally Stable Extremal Regions (MSER) algorithm, which performs very well in finding stable regions in images that are robust under changing levels of contrast and lighting. Following the initial preprocessing phases, including contrast stretching and noise reduction, the adaptive thresholding operation produced a binary image, paving the way for the MSER algorithm.

MSER algorithm was used to identify the connected regions likely to represent a single character. Due to the inconsistency in the inscriptions—e.g., uneven surfaces and partial deterioration—MSER's capability to identify regions that are stable across various intensity thresholds worked very well to identify meaningful character boundaries. The identified regions were subsequently filtered using size constraints to ensure that only regions of proper dimensions were preserved. This step filtered out noise and irrelevant features, like extremely small or extremely large areas that could not possibly be a single character.

Each viable area was then cropped, padded to have square dimensions, and resized to a fixed resolution of 128x128 pixels. This normalization allowed the following steps, like inpainting and classification, to process the segmented characters in a consistent manner, making the overall model more robust.

This segmentation pipeline, combined with the previous preprocessing, guarantees that every character is cleanly isolated, retaining its structural integrity despite the degradation that is inherent in historical inscriptions.

4. Model Creation:

For the model, we will employ a hybrid strategy with ResNet50 for feature extraction and a Random Forest classifier for final classification, taking advantage of deep learning's strength in complex feature capture and machine learning's stability for correct predictions.

a) ResNet50:

For Brahmi script classification, we use ResNet50, a deep convolutional neural network (CNN) model that relies on residual connections to make it possible to train networks that are very deep. The residual connections help it to overcome the vanishing gradient issue, hence proving to be effective in handling tasks as complex as character recognition. It features several convolutional blocks with residual connections that allow gradients to flow more easily through backpropagation.

We use ResNet50 as a feature extractor, ignoring the first classification layers and replacing them with a custom head. The custom head includes Global Average Pooling, Dropout, and a Dense layer with softmax activation so that the model can produce Brahmi script classes. The ResNet50 layers are first frozen so that the pre-trained features of ImageNet are not lost, and only the custom layers are trained. A learning rate of $1\mathrm{e}-4$ is specified for the fine-tuning stage to fine-tune the model's performance on the Brahmi dataset. Following preliminary training, the last 20 layers of ResNet50 are unfrozen to fine-tune so that the model can fit more specifically to the Brahmi characters. A lower learning rate $1\mathrm{e}-5$ is employed during fine-tuning to avoid overfitting and to enable the model to converge properly

To enhance the model's capacity to pay attention to significant features, we employ attention mechanisms such as CBAM (Convolutional Block Attention Module) and SE-blocks (Squeeze-and-Excitation).

CBAM also encourages model's spatial and channel-wise feature attention by sequential concatenation of a spatial attention module and a channel attention module. The model can focus on the most significant features spatially and channel-wise, thereby enhancing its discrimination power between the concerned aspects of the input images, e.g., various Brahmi characters.

SE-blocks, on the other hand, re-tune the channel activations using a squeeze operation that computes global information over channels and an excitation operation that re-scales the weight of each channel. This enables the model to focus on the most important channels, enhancing its discriminative capacity in the process of character recognition.

These attention mechanisms together allow the model to pay more attention to important features and thus improve its performance in identifying Brahmi characters even in poor conditions of degradation or noise.

b) Random Forest:

The hybrid model for Brahmi script classification combines the feature extraction ability of ResNet50 with the Random Forest classifier. ResNet50 is used as a feature extractor, and the output of the Global Average Pooling layer is passed as input to the Random Forest classifier for the classification purpose. The approach successfully extracts complex patterns of the Brahmi characters while minimizing the amount of retraining needed. This process is mathematically represented by Equation (2).

Feature Extraction:

$$\mathrm{F} = \mathrm{f}_{\mathrm{ResNet50}}(\mathrm{x}) \qquad (2)$$

Here, x denotes the input image and F represents the extracted feature vector.

Classification:

These features F are then classified using a Random Forest. A Random Forest aggregates the decisions of multiple decision trees to produce the final output. The prediction probability for a class c given the features F is computed as shown in Equation (3).

$$P(y = c \vee F) = \frac{1}{T}\sum_{t=1}^{T} h\,(F) \qquad (3)$$

where T is the number of trees in the ensemble, and $h(t)(F)$

denotes the prediction of the t-th decision tree.

To reduce the feature dimensionality and prevent overfitting, Principal Component Analysis (PCA) is applied. PCA processing maintains 95% of the feature variance, minimizing the loss of informative information in the feature space while optimizing it. Low-dimensional features are utilized to train a Random Forest classifier with 300 trees. Class imbalance is resolved by computing and applying class weights during training.

The model is also verified against precision, recall, accuracy, and F1-score to ensure the Brahmi characters are being accurately identified. There is also an out-of-distribution (OOD) detection feature. In the event the classifier confidence in the prediction is below a certain threshold, the input is marked as "special characters" in order to allow the system to properly handle unknown or distorted characters.

This ensemble approach leverages the high performance of ResNet50 and Random Forest and enhances the efficacy of the model in classifying Brahmi script character classes from degraded and clean images. The feature extraction, dimensionality reduction, and ensemble classification together provide a robust and consistent system that is able to handle real-world Brahmi inscription variability effectively.

Algorithm 1: Hybrid Character Prediction	
Require: Preprocessed image	
Output: Predicted character label	
1.	x = ResNet_FeatureExtractor(I) z = PCA(x) y_dl = ResNet_Classifier(I) y_rf = RandomForest_Classifier(z)

2.	if max(y_dl) >= theta_resnet:
	    return argmax(y_dl)
	elif max(y_rf) >= theta_rf:
	    return argmax(y_rf)
	else:
	    return "Special Character"

End	

V. RESULTS AND DISCUSSIONS

1. GAN-Inpainted Image

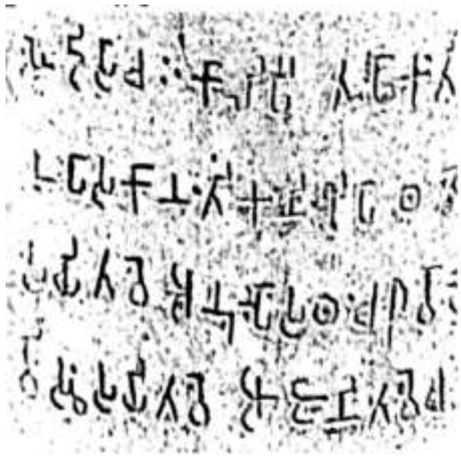

Fig. 2. Shows an enhanced image via in-painting for readability.

2. MSER Extracted Characters

Fig. 3. Characters Extracted Via MSER segmentation for recognition

3. Model Training

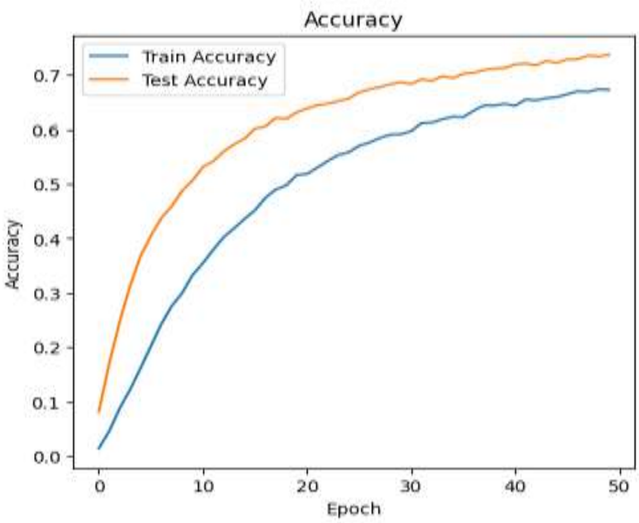

Fig. 4. Training and validation accuracy curve of the ResNet model for Brahmi character classification.

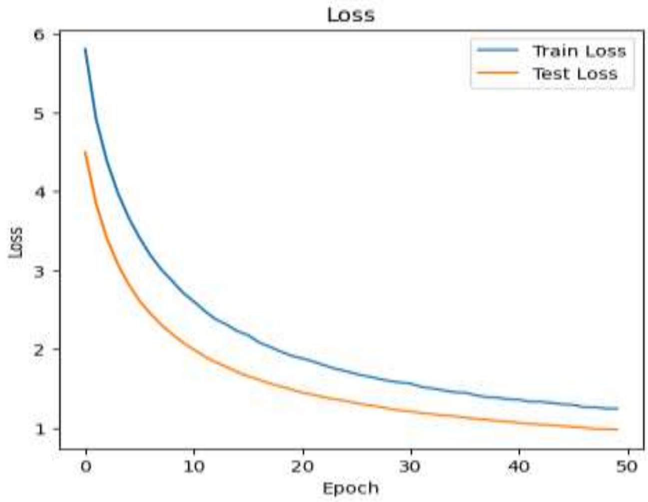

Fig. 5. Training and validation loss curves of the ResNet model.

4. Hybrid Model Performance Metrics: Precision, Recall and F1-Score

The ResNet50-Random Forest ensemble model was able to attain 96.5% accuracy for Brahmi script character classification. The model metrics, i.e., precision, recall, and F1-score, remained similar for both macro and weighted average, meaning it was a well-balanced performance for every class. All the above findings affirm the model to be very proficient in accurate and reliable Brahmi script character classification.

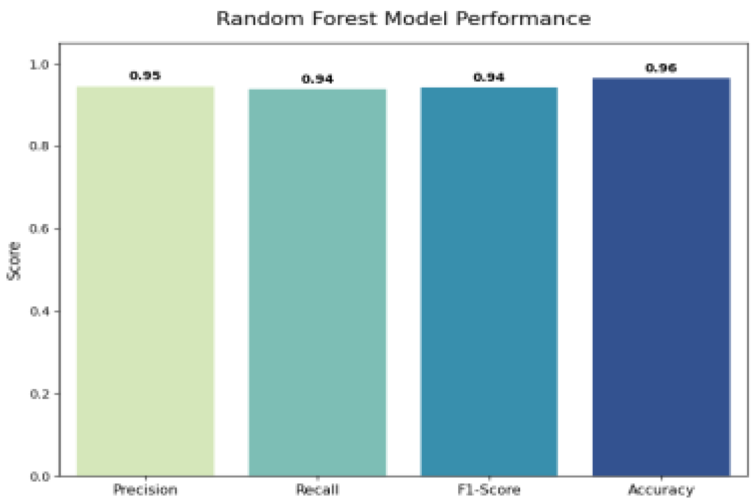

Fig 6: Precision, Recall, and F1-Score for Model Performance

5. Prediction Results and Analysis

The hybrid model (ResNet50 + Random Forest) proposed was tested on a test dataset of segmented Brahmi character images from actual inscriptions. The model recorded an accuracy of 96.5%, which reflects its stability in addressing intricate real-world situations encompassing erosion, cracks, and changes in lighting conditions.

Applying a Random Forest classifier to ResNet50 deep features enabled the model to maintain both precision and generalization. The model excelled particularly in typical character classes but sometimes incorrectly classified heavily degraded or incomplete characters, as might be expected based on the type of ancient inscriptions.

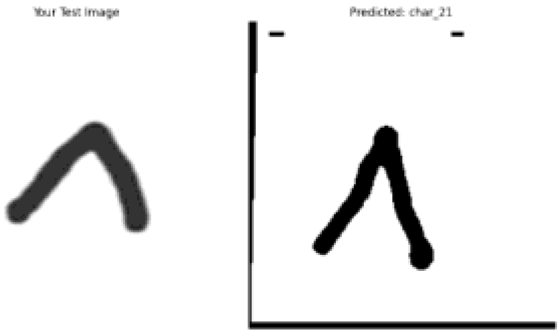

Fig 7: Shows the test image fed into the model and the predicted character

6. Comparison with existing models

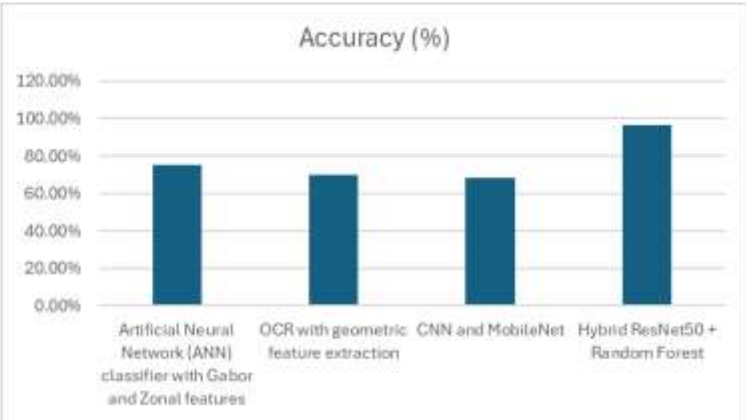

Fig 8: Comparison of proposed methodology with other existing models

These research papers point to the difficulties in the recognition of Brahmi script, particularly when it comes to ancient inscriptions and small datasets. The achievements of these studies—68.3% by Wijerath et al.[16], 70% by Gautam and Chai[17], and 75% by Sowmya and Kumar[17]—attest to the difficulty of the task. Your model's attainment of 96.5% accuracy attests to an even greater leap in this area, the success of your strategy in addressing the intricacies of Brahmi script recognition

7. Special Character Recognition

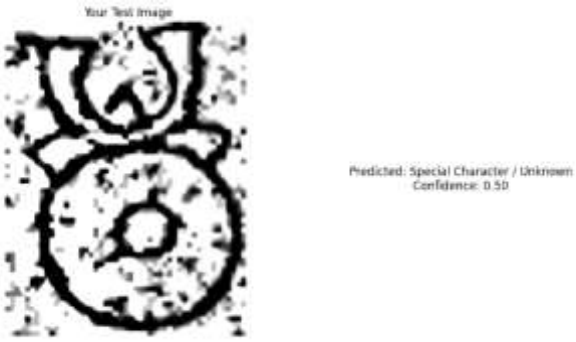

Fig 9: Special Character detected using confidence thresholding — preventing misclassification as known Brahmi characters

Special character detection is obtained by imposing a confidence threshold on the prediction probabilities of the model. [20] When an image is classified, class probabilities are produced by the hybrid model. If the maximum confidence score is less than a threshold set beforehand (for example, 0.6), the image is tagged as a "Special Character" rather than misclassified. This prevents unknown or non-standard characters from being allocated to a regular Brahmi class.

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8. Handling of Missing Characters

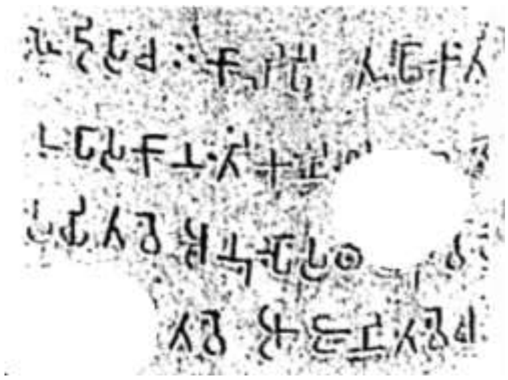

Fig 10: Brahmi script inscription exhibiting missing and worn-off characters due to degradation.

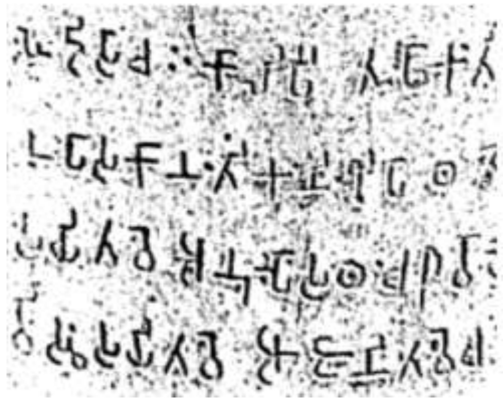

Fig 11: In-painted Brahmi script inscription generated using GAN-based pre-processing.

To deal with the issue of missing or worn-off characters in Brahmi script images as shown in Figure 10, GAN-based inpainting is used as a preprocessing technique as shown in Figure 11. This method fills in missing or worn-off character strokes, allowing improved maintenance of structural integrity. By restoring such characters prior to their processing through the feature extraction and classification pipeline, the model provides enhanced recognition performance, particularly in the case of ancient and deteriorated inscriptions

VI. Conclusion

In this work, a hybrid deep learning pipeline for Brahmi script recognition is proposed that effectively addresses the issues of ancient inscriptions such as surface erosion and missing strokes. Through the integration of GAN-based inpainting, MSER segmentation, and a ResNet50 + Random Forest ensemble model, the system attained a robust classification accuracy of 96.5%. [19] The findings identify the strength of integrating restoration, attention mechanisms, and ensemble learning in historical script analysis that provides a robust platform for future digital epigraphy research.

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