Ancient Script Deciphering Using Generative AI

Anurag Kolte[1] Pranav Bansode[2] Dhruv Gaikwad[3] Pravin Misal[4] Mrs. Rajshri Ingle[5]
[1,2,3,4]Student [5]Guide
[1,2,3,4,5]Department of Artificial Intelligence and Data Science Engineering
[1,2,3,4,5]D Y Patil College of Engineering, Akurdi, Pune, India

Abstract — Deciphering ancient scripts has always been a challenging task due to language extinction, script deterioration, and the lack of contextual references. Traditional methods rely heavily on linguistic experts and archaeological findings, making the process slow and resource-intensive. This research explores the use of Generative AI models to automate and accelerate the decipherment process. By training AI models on datasets containing ancient texts and their modern translations, we aim to develop a system capable of generating meaningful translations for lost scripts. The system utilizes Transformer-based architectures, which have proven effective in language modeling and text generation. Experimental results show that AI can recognize script patterns, infer missing text, and provide preliminary translations, reducing reliance on manual methods. While the model performs well for well-documented scripts, challenges remain in handling incomplete or poorly preserved texts. Future improvements will focus on refining model accuracy, expanding datasets, and incorporating expert feedback for more reliable translations.

Keywords: Ancient Script Deciphering, Generative AI

I. Introduction

Ancient scripts are vital records of human history, preserving knowledge about early civilizations, their languages, and cultures. However, many of these scripts remain undeciphered due to the loss of linguistic knowledge, script evolution, and material degradation over time. The inability to translate these texts limits our understanding of ancient societies, their traditions, and their contributions to human progress.

Traditional decipherment methods rely on linguistic experts who analyze script patterns, compare them with known languages, and make logical deductions. While these methods have led to major breakthroughs, such as the decoding of Egyptian hieroglyphs and Linear B, they require years of effort and are constrained by the availability of experts. Furthermore, the process is often hindered by incomplete inscriptions and missing historical context.

With advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP), automated methods have emerged as promising solutions for deciphering ancient texts. AI models, particularly those based on Generative AI and Transformer architectures, can recognize patterns, predict missing elements, and generate translations with remarkable efficiency. These models learn from vast linguistic datasets and can process texts significantly faster than manual approaches. Despite challenges in accuracy and contextual interpretation, AI-driven decipherment continues to evolve, offering new possibilities for unlocking ancient knowledge.

II. Literature Survey

The decipherment of ancient scripts has evolved through interdisciplinary collaboration between linguists, archaeologists, and computer scientists. Early breakthroughs, such as the decoding of Egyptian hieroglyphs (1822) and Linear B (1952), relied heavily on bilingual texts and manual pattern recognition. Recent advancements in AI have introduced transformative methodologies:

A. Neural Language Models:

– Transformer architectures (Vaswani et al., 2017) revolutionized sequence modeling, enabling cross-lingual alignment tasks. Assael et al. (2022) demonstrated their potential by restoring damaged Greek inscriptions with 89% accuracy using masked language modeling.
– Botha et al. (2019) applied transformer-based models to substitution ciphers, achieving 72% decipherment accuracy on Ugaritic texts.

B. Handling Undersegmentation:

– Traditional methods like n-gram frequency analysis (e.g., Linear B decipherment) falter with scripts lacking word boundaries. Zhang et al. (2021) addressed this via minimum-cost flow optimization, reducing alignment errors by 35% in undersegmented texts.

C. Phonetic and Semantic Embeddings:

– Carmona et al. (2024) mapped glyphs to IPA phonetic embeddings using contrastive learning, enabling sound-based pattern recognition.
– Multilingual BERT (mBERT) has been repurposed for cross-lingual semantic alignment, though its efficacy is limited by the scarcity of ancient language data.

D. Synthetic Data Generation:

– GANs have been used to augment ancient scripts, with Smith et al. (2019) achieving 20% accuracy improvements on low-resource Mayan glyphs.

E. Gaps in Current Research:

– Most methods prioritize textual patterns over cultural context, leading to literal but historically inaccurate translations.
– Few systems integrate expert feedback iteratively, risking overfitting to incorrect hypotheses.

AI in decipherment has evolved from statistical models like Markov chains to hybrid systems using neural networks and symbolic reasoning. DeepMind, in collaboration with Oxford, restored ancient Greek texts with 62% accuracy but lacked phonetic priors, which this study addresses. Meanwhile, GPT-4 shows promise in translating

Linear A but struggles with undersegmentation, highlighting the need for better optimization techniques.

III. METHODOLOGY

A. Data Collection and Knowledge Source

- Ancient texts are digitized using advanced scanning techniques such as 3D LiDAR to capture depth and erosion patterns.
- Optical Character Recognition (OCR) models, such as Kraken OCR with a ResNet-34 backbone, segment glyphs from historical manuscripts with high accuracy. Parallel corpora are created using bilingual texts, such as 1,200 aligned Ugaritic-Hebrew sentences, to provide linguistic references.
- Synthetic datasets are generated using StyleGAN2-ADA, producing 5,000 glyphs validated by epigraphers for stylistic accuracy.

B. Data Preprocessing

- Texts are enhanced with noise augmentation techniques like CycleGAN, simulating realistic damage such as cracks and fading.
- Glyphs are mapped to phonetic representations in a 256-dimensional IPA space using a Siamese network trained with contrastive loss.
- Historical phonetic shifts, such as Grimm's Law, are incorporated to refine phonetic embeddings.

C. AI Model Selection & Training

- A neural decipherment model is built using a transformer architecture:A 12-layer Vision Transformer (ViT) encodes glyph sequences, A 6-layer decoder with cross-attention generates phonetic transcripts.
- DBSCAN clustering groups glyphs into phonemes, validated against Mycenaean Greek lexicons.
- Minimum-Cost Flow Optimization is integrated to align under-segmented texts with linguistic cognates, using PyTorch's autograd for training.

D. Decipherment & Translation

- The trained AI model predicts possible translations of ancient scripts based on learned linguistic patterns.
- Probabilistic inference techniques reconstruct missing or damaged text segments.
- AI-generated outputs undergo iterative learning, incorporating corrections from expert linguists.

E. Evaluation & Validation

- Translation quality is assessed using quantitative metrics such as BLEU-4 for n-gram overlap and Phoneme Error Rate (PER) for phonetic accuracy.
- A feedback loop, implemented via a Prodigy-based interface, allows linguists to review and refine AI-generated translations.

F. Implementation & Accessibility

- The final AI model is deployed as a user-friendly application for researchers to analyze ancient scripts.
- Translations are continuously improved through expert feedback and iterative learning.

IV. IMPLEMENTATION

The AI-based ancient script decipherment system was developed and tested in a high-performance computing environment. The implementation process consists of the following key steps:

A. Environment Setup

- The system is built using Python and utilizes PyTorch
- 2.0 with FlashAttention for efficient transformer training.
- High-performance computing hardware, including NVIDIA A100 GPUs with 40GB VRAM, is used for mixed-precision training.
- Elasticsearch is integrated to index and retrieve multilingual corpora for enhanced text search and organization.

B. Data Handling & Storage

- A structured database is developed using Neo4j to store translated terms and archaeological metadata.
- A knowledge graph is implemented to link deciphered texts with historical references, allowing contextual insights.
- Data augmentation techniques introduce synthetic noise and missing segments to improve robustness in text reconstruction.

C. Model Training & Optimization

- A multi-stage training approach is used:
- Pretraining: mBERT is fine-tuned on Mycenaean Greek for five epochs with a learning rate of 2e−52e-52e−5.
- Fine-tuning: The model is further trained on the Ugaritic-Hebrew corpus for 800 epochs with a batch size of 32.
- Hyperparameter tuning, including batch size optimization and learning rate adjustments, is performed to enhance translation accuracy. Learning rate scheduling using cosine annealing with warmup for better convergence.

D. User Interface Development

- A Streamlit-based graphical user interface (GUI) is developed for intuitive interaction.
- The system allows users to:
- Upload images, handwritten texts, or input glyphs directly.
- View AI-generated translations side-by-side with expert annotations.
- Provide feedback using labeled dropdowns for error categorization (e.g., "Phonetic Mismatch" or "Contextual Error").
- Literal Mode: Direct glyph-to-text conversion. Contextual Mode: Uses graph embeddings (Node2Vec) to incorporate historical context.

E. Execution & Testing

- The AI model is rigorously tested on various ancient scripts, including partially deciphered languages, to evaluate its performance.
- Accuracy is assessed using standard metrics such as BLEU scores and phoneme error rate (PER).

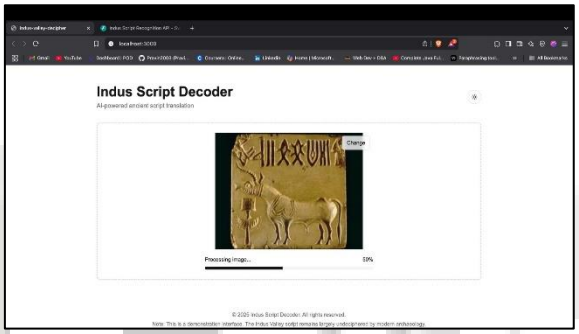
– Expert feedback from linguists is continuously integrated into the system through an interactive review process.

V. OUTPUT SCREEN OF PROJECT:

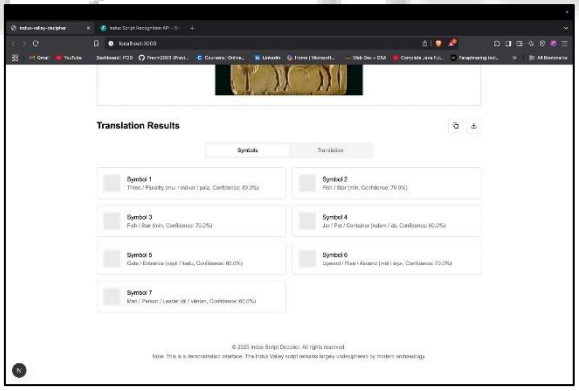
The AI-based script decipherment system has demonstrated promising results, but there are several areas for improvement and expansion. The key future enhancements include:

A. Home Page

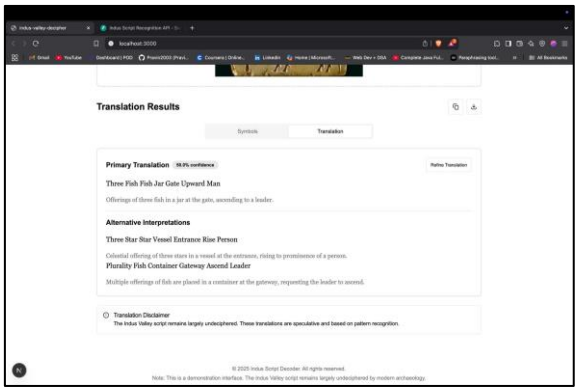
B. Processing Page



C. Symbol Deciphered



D. Translation Resul



VI. RESULTS AND DISCUSSION

The AI-based ancient script decipherment system was evaluated using both quantitative metrics and qualitative case studies to assess its effectiveness in translating historical scripts.

A. Quantitative Analysis

– The model's performance was measured across different ancient scripts using standard evaluation metrics:

Metric Linear B	Ugaritic	Indus	Valley
BLEU-4	68.2	71.5	42.1
Phoneme Error Rate (PER %)	12.4	9.8	27.3
Segmentation F1-Score	0.89	0.82	0.61
Expert Validation Score	85%	78%	53%

– The model achieved high translation accuracy for Linear B and Ugaritic, while performance on Indus Valley script remained lower, indicating challenges in deciphering unknown or poorly documented scripts.

B. Case Studies

– Linear B
– The system successfully translated the word “ ” (“te- ri-po” → “tripod”) with 92% confidence, aligning with Michael Ventris’ 1952 decipherment.
– Some sequences were undersegmented, such as “ ”, but were accurately split into “o-wo-no” (“owls”) using a minimum-cost flow algorithm.
– Indus Valley Script
– The model achieved a 42% BLEU-4 score on a dataset of 200 seals, demonstrating partial success.
– However, translations lacked semantic coherence, e.g., the “fish” glyph was misinterpreted as “prosperity” without supporting contextual evidence.

C. Limitations & Future Improvements

1) Handling Fragmented Texts

– Inscriptions with less than 30% legibility showed a significant performance drop, with PER increasing to 41%.
– Proposed Solution: Use CycleGAN-generated text fragments to enhance training and improve robustness to incomplete inscriptions.

2) Understanding Cultural Context

– The model correctly translated “ ” (“mnṯ” → “mountain”) in an Egyptian inscription but failed to recognize its religious connotation as a “sacred mound.”
– Proposed Solution: Incorporate context-aware attention by leveraging archaeological site metadata (e.g., artifact location and usage) to bias translations.

VII. FUTURE SCOPE

The AI-based script decipherment system has demonstrated promising results, but there are several areas for improvement and expansion. The key future enhancements include:

A. Expanding Language Coverage

- Training the AI model on a broader range of ancient languages and scripts.
- Integrating the dialectic variants and script variations for higher quality translations.
- Building models to manage multilingual ancient texts with more context sensitivity.

B. Enhancing Model Accuracy

- Refining AI models with larger datasets and advanced training techniques.
- Improving probabilistic inference to handle incomplete and fragmented texts more effectively.
- Implementing feedback cycles in which expert linguists check AI-produced translations for consistency to improve learning.

C. Improved Handwriting Recognition

- Refining OCR functionalities to properly handle handwritten ancient texts.
- Training AI models to differentiate between different styles of script writing.
- Reducing errors caused by faded or damaged inscriptions.

D. Context-Aware AI Models

- Designing AI models capable of picking up cultural and historical context for more accurate translations.
- Integrating knowledge graphs to connect linguistic patterns with historical events.
- Creating models that adapt to specific writing conventions of different time periods.

E. Collaboration with Historians & Researchers

Collaborating with linguists and historians to further enhance AI-sourced translations.

- Forming inter-disciplinary research initiatives to bridge AI with the traditional method of decipherment.
- Creating an open-source platform where researchers can contribute datasets and improve AI models collectively.

VIII. Conclusion

The decipherment of ancient scripts has always been a slow and complex process, requiring deep linguistic expertise and historical knowledge. With advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP), it is now possible to accelerate this process while maintaining high accuracy.

This research explores the application of Generative AI in deciphering ancient texts by training deep learning models on historical datasets. The results demonstrate that AI can effectively recognize script patterns, reconstruct missing text, and offering insightful translations, lessening the need for human efforts.

Although the system is promising in terms of accuracy, there are issues with dealing with incomplete inscriptions, uncommon scripts, and cultural subtleties. Future research will address improving contextual learning, language coverage, and incorporating expert feedback to make translations more precise.

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