CHAPTER 1
INTRODUCTION

Tamil, one of the world's oldest living languages, holds an unparalleled position in the history of human civilization. With roots stretching back more than two thousand years, Tamil has not only evolved as a spoken and written language but also as a medium for recording cultural, political, and religious developments. Inscriptions, palm-leaf manuscripts, temple writings, and stone engravings from ancient Tamil Nadu offer a glimpse into the lives, beliefs, and achievements of the people who lived in different eras. These ancient scripts, carved or inscribed with remarkable precision, carry invaluable information about the traditions, literature, economy, and governance of their time. However, the passage of centuries has caused many of these records to fade, erode, or become partially damaged, making manual interpretation difficult. Scholars and researchers have long attempted to preserve and decode these inscriptions, but the process remains time-consuming and prone to errors due to the complexity of the ancient script and the limited number of experts capable of reading it.

The evolution of the Tamil script from its earliest forms such as Tamil-Brahmi and Vatteluttu to the modern Tamil script used today has further widened the gap between ancient and contemporary readers. Each stage in this evolution introduced subtle yet significant changes in the shape and structure of characters. While modern Tamil script is standardized and digitally represented, the older forms are diverse, irregular, and often artistically stylized. Many inscriptions contain incomplete or worn-out letters, where identifying even a single character requires deep linguistic and historical expertise.

As a result, preserving and decoding these inscriptions is not only a linguistic challenge but also a cultural mission, as they represent the collective memory of Tamil civilization.

In recent decades, the rapid growth of technology, especially in the field of artificial intelligence, has created new opportunities to address this long-standing challenge. Image processing, deep learning, and computer vision have enabled machines to perform complex recognition tasks with remarkable accuracy. Technologies that were once limited to industrial or academic research are now being applied to historical preservation, allowing for automated recognition and translation of ancient scripts. This integration of technology and tradition has opened the door to a new era in cultural preservation. Through advanced image recognition models, it is possible to train systems to identify, interpret, and translate ancient Tamil inscriptions into modern Tamil or even English, thus making them accessible to a much wider audience.

The importance of decoding ancient Tamil texts extends beyond academic curiosity. These inscriptions are vital historical documents that record royal decrees, religious endowments, social customs, trade relations, and philosophical ideas. They provide first-hand evidence of the political structures, economic systems, and cultural values of early Tamil societies. Understanding these texts helps reconstruct lost histories and fills gaps left by mainstream historical narratives. Furthermore, it contributes to the preservation of linguistic diversity and strengthens the connection between present and past generations. By reviving access to ancient Tamil literature, we ensure that the voices of our ancestors continue to be heard in the digital age.

Despite these opportunities, decoding ancient Tamil characters using technology is not a straightforward task. Unlike modern printed text, ancient inscriptions exhibit inconsistencies caused by hand-carving methods, environmental damage, and erosion. The shapes of letters vary significantly based on region, material, and the artisan's style. Some inscriptions even mix scripts from different eras, adding another layer of complexity. Existing Optical Character Recognition (OCR) systems are not equipped to handle such variations, as they are trained primarily on clean, high-quality printed text. Therefore, traditional OCR models often fail to recognize or correctly classify ancient Tamil characters. To overcome these challenges, deep learning models, particularly convolutional neural networks (CNNs), offer a more effective approach because they can learn complex visual patterns and adapt to varying input conditions.

Developing a reliable system for ancient Tamil character recognition involves several stages, including image acquisition, preprocessing, segmentation, feature extraction, and classification. High-resolution images of inscriptions or manuscripts are first collected and cleaned to remove noise, enhance contrast, and sharpen edges. The images are then segmented into individual characters or regions of interest. The model learns distinctive features from each character—such as stroke patterns, curvature, and relative proportions—using deep learning algorithms. Finally, it predicts the corresponding modern Tamil letter based on its training data. Over time, as the dataset grows and the model becomes more refined, the system achieves higher levels of accuracy and reliability. This process not only simplifies character recognition but also provides a foundation for automated translation and linguistic analysis.

The potential applications of such a system are far-reaching. Museums and archaeological departments can use it to digitize and catalog inscriptions systematically. Researchers can employ it to study linguistic evolution or identify regional variations in script style. Educational institutions can integrate it into their history and language departments to teach students about ancient Tamil culture in an interactive manner. Moreover, the decoded data can be linked with digital archives and made available online, allowing global access to Tamil heritage. Such initiatives would not only preserve ancient Tamil knowledge but also promote cultural awareness and appreciation on an international scale.

This research aims to bridge the gap between ancient Tamil inscriptions and modern readers through the power of technology. By combining computer vision and deep learning, the system aspires to decode and translate ancient Tamil scripts efficiently and accurately. It contributes to both linguistic research and heritage preservation by ensuring that invaluable historical texts are not lost to time. The success of this approach could serve as a model for other ancient languages facing similar challenges, demonstrating that modern technology can coexist with traditional scholarship to preserve the world's oldest forms of expression.

LITERATURE SURVEY

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction to Script Recognition and OCR

Script recognition has been a significant area of research in computer vision and pattern recognition for several decades[22]. The process involves the identification and digital interpretation of characters from various scripts, enabling computers to read and process written or printed text automatically. Optical Character Recognition (OCR) technology was one of the earliest applications of pattern recognition and has since evolved with advances in machine learning and deep learning[23]. Tools such as Tesseract OCR, initially developed by Hewlett-Packard and later maintained by Google, represent milestone achievements in the field[23] [36]. Despite these advancements, OCR systems have primarily been optimized for modern printed scripts and often fail when dealing with ancient scripts, which exhibit irregular shapes, degraded textures, and stylistic variations[25] [30].

Researchers have pointed out that the success of OCR depends heavily on the quality of the input image, the consistency of the script, and the complexity of character design[22] [37]. Ancient scripts like Tamil, which have evolved over millennia, pose unique challenges because of their ornamental forms and the degradation of historical materials[30]. While early OCR models relied on rule-based segmentation and heuristic methods, modern systems employ complex algorithms and neural networks for improved feature extraction and classification[10] [39].

2.2 Research on Tamil Script Recognition

Tamil script, being one of the oldest and most intricate writing systems of South Asia, has been a central focus in linguistic and computational research[35]. Studies by Mahadevan[30] and Zvelebil[1] have traced the evolution of Tamil writing from its earliest inscriptions to the modern era, emphasizing the historical and cultural significance of its preservation. Early computational efforts for Tamil character recognition used template matching, edge detection, and morphological operations to identify script patterns[24]. However, these techniques were highly sensitive to noise and variations in character design[25].

The introduction of machine learning algorithms, including Support Vector Machines (SVMs) and k-Nearest Neighbors (kNN), marked an important shift in Tamil OCR development[26]. These models improved accuracy but lacked robustness when dealing with ancient or degraded manuscripts[25] [46]. Later research, such as that of Vijayarani and Tamilselvi[25], incorporated heuristic rules for ancient Tamil epigraphy, while Anitha and Deepa[24] explored feature-based segmentation approaches for handwritten Tamil characters. More recently, studies by Kumar and Arvind[49] and Jeyakumar and Raghavan[47] have adopted deep learning techniques to enhance recognition rates for ancient Tamil inscriptions, demonstrating significant improvement over traditional systems.

2.3 Deep Learning for Script Recognition

Deep learning has revolutionized character recognition systems through the introduction of Convolutional Neural Networks (CNNs)[10] [12]. CNNs excel in identifying spatial hierarchies in visual data, making them ideal for distinguishing complex character features even in degraded conditions[37] [40]. Further enhancement has been achieved using hybrid architectures that combine

CNNs with Long Short-Term Memory (LSTM) networks, allowing the system to learn both spatial and sequential dependencies[28] [41]. The CRNN (Convolutional Recurrent Neural Network) architecture, introduced by Shi, Bai, and Yao[28] [44], has become a foundational model for sequence-based recognition tasks, including text line detection and scene text interpretation.

Researchers like LeCun[10] and Goodfellow[11] [39] have emphasized the importance of hierarchical feature learning in visual recognition. These concepts have been applied effectively in OCR frameworks that target multilingual and historical document analysis[29]. Advanced optimization algorithms such as Adam[42] have further improved convergence in deep learning models, while transfer learning techniques have allowed the adaptation of pre-trained networks to smaller datasets relevant to ancient scripts[49].

2.4 Challenges in Ancient Script Recognition

Ancient script recognition presents several persistent challenges, primarily related to data scarcity, image degradation, and stylistic variability[26] [30]. Historical manuscripts are often damaged or incomplete, making accurate recognition difficult[31] [48]. Furthermore, variations in inscription styles across different time periods and regions add complexity to the recognition process[30] . Unlike modern printed documents, ancient scripts lack standardized spacing and formatting, complicating segmentation and classification tasks[24].

To address these limitations, researchers have experimented with synthetic dataset generation and data augmentation techniques[38], as well as transfer learning approaches that leverage knowledge from modern script datasets[49]. Crowd-sourced labeling and expert annotation have also been adopted to expand

and validate ancient text datasets[32]. Despite these efforts, there remains a pressing need for comprehensive datasets dedicated to ancient Tamil characters[33] [46].

2.5 Existing Systems and Tools

Several OCR platforms have contributed significantly to the digitization of historical texts. Tesseract OCR[23] [36], one of the most widely used engines, supports numerous languages but struggles with ancient scripts unless retrained using custom datasets. Transkribus[29] provides an advanced framework for handwritten text recognition (HTR) in historical manuscripts, while Kraken OCR[29] offers an open-source solution designed specifically for historical and multilingual document processing.

In the Indian context, systems like Project Madurai[32] [45] have undertaken large-scale digitization of Tamil literature, making classical texts accessible for computational research. However, these tools still require adaptation for ancient Tamil forms, as they often fail to capture the structural nuances of the Vatteluttu and early Tamil-Brahmi scripts[35] [30]. Studies by Suresh and Balasubramanian[46] and Prasad and Ghosh[48] have shown that hybrid CNN-based systems outperform traditional OCR in handling such scripts, though challenges remain in achieving semantic-level translation.

2.6 Related Works on Indic Scripts

Indic scripts, including Devanagari, Bengali, and Tamil, share structural and phonetic similarities, making cross-script research valuable for OCR development[15] [26]. Research on Devanagari OCR has demonstrated that combining CNNs with sequential models significantly enhances recognition accuracy[28] [41]. Similar hybrid approaches have been applied to Tamil OCR with encouraging results[24] [46].

In recent years, researchers have explored the use of Generative Adversarial Networks (GANs) to restore degraded ancient scripts[29] and hybrid attention-based networks for text translation[29 47]. Palm-leaf manuscript digitization projects have also benefited from these techniques, as they allow the recovery of faint inscriptions and improve character boundary detection[30 31]. Such innovations have paved the way for automated recognition of ancient South Indian scripts, but complete end-to-end translation systems remain rare[33 48].

2.7 Gaps in Existing Research

Despite remarkable progress, there remains a considerable gap in fully automated systems capable of translating ancient Tamil inscriptions into modern Tamil [33 47 50]. Most existing frameworks focus primarily on character-level recognition without addressing contextual understanding or semantic reconstruction [34 48]. Consequently, while they achieve satisfactory accuracy in isolated glyph detection, they often fail to produce meaningful and grammatically coherent Tamil sentences. The absence of linguistic integration modules or grammar-based post-processing pipelines limits these systems to surface-level recognition rather than complete textual interpretation [33 45].

A major obstacle continues to be the scarcity of standardized and annotated datasets for ancient Tamil [36 41]. Existing datasets are often institution-specific, small in scale, and inconsistent in labeling formats [37 42]. Since most inscriptions are retrieved from temple walls, copper plates, or palm-leaf manuscripts, their image quality is highly variable due to erosion, discoloration, and incomplete carvings [38 44]. The resulting degradation severely affects OCR accuracy and leads to frequent misclassifications, particularly for characters with subtle stroke differences.

TECH STACK

CHAPTER-3
TECH STACK

The Ancient Tamil Decoding System is built upon a sophisticated and well-integrated technology stack designed to handle complex image processing, machine learning, and character recognition tasks efficiently. The system primarily utilizes YOLOv8, Roboflow, and Google Colab as its core technological components, supported by additional frameworks and tools for data handling, visualization, and deployment. Each component in this stack has been carefully selected to ensure high performance, scalability, and ease of development. The integration of these technologies forms a seamless workflow that transforms raw images of ancient Tamil inscriptions into modern Tamil-readable text with precision and reliability.

At the foundation of the system lies YOLOv8 (You Only Look Once Version 8), a state-of-the-art object detection and image recognition model developed by Ultralytics. YOLOv8 is chosen for its exceptional speed, accuracy, and flexibility in detecting complex visual patterns, making it ideal for recognizing ancient Tamil letters that vary in shape, size, and clarity. The model's ability to perform real-time detection with high accuracy allows it to identify and classify characters even in degraded or noisy image conditions. The convolutional neural network (CNN) architecture of YOLOv8, coupled with advanced optimization techniques, provides superior feature extraction and learning capabilities. This ensures that subtle details in ancient inscriptions—such as curves, loops, and dots—are effectively captured and interpreted. YOLOv8's modular design also supports easy customization and fine-tuning, enabling developers to adapt the model to specific datasets without significant reconfiguration.

To support the training and dataset management process, the system leverages Roboflow, an intuitive and powerful platform for dataset preparation, augmentation, and annotation. Roboflow plays a crucial role in organizing and preprocessing image datasets before they are fed into the YOLOv8 model. Using Roboflow, all ancient Tamil inscription images are uploaded, labeled, and categorized efficiently. The tool provides a convenient web interface that simplifies the annotation process, allowing for accurate bounding box creation around each Tamil character. Furthermore, Roboflow automatically handles data augmentation tasks such as rotation, flipping, brightness variation, and noise addition. These augmentations significantly increase the diversity of training data, allowing the model to generalize better to unseen images. The platform also facilitates seamless dataset versioning and API-based integration with Google Colab, making it easier to retrieve updated datasets directly during training sessions. This automation eliminates manual dataset management and ensures that the training pipeline remains consistent and reproducible.

The training and evaluation phase of the model are performed in Google Colab, a cloud-based environment that provides free access to high-performance GPUs and TPUs. Google Colab allows developers to execute Python code in a Jupyter Notebook-style interface, enabling interactive experimentation with machine learning models. The platform is particularly suited for training deep learning architectures like YOLOv8, which require extensive computational resources. By utilizing GPU acceleration, Colab drastically reduces model training time and enables efficient handling of large-scale datasets. The integration with Google Drive also allows smooth synchronization of datasets, model checkpoints, and output results. This cloud-based approach not only enhances productivity but also provides a cost-effective solution for researchers who do not have access to

dedicated GPU hardware. Additionally, Colab's collaborative features allow multiple contributors to work on the same notebook simultaneously, promoting teamwork and continuous development.

The entire system is implemented using Python, a highly versatile programming language that offers a wide ecosystem of machine learning libraries. Python provides seamless integration with YOLOv8 and Roboflow APIs, simplifying model training, evaluation, and deployment. Supporting libraries such as NumPy, Pandas, and OpenCV are used for numerical computation, dataset manipulation, and image preprocessing respectively. OpenCV is particularly useful for operations such as grayscale conversion, thresholding, edge detection, and noise filtering, all of which are essential for improving the clarity of input images before feeding them into the YOLOv8 model. These preprocessing steps ensure that the neural network receives high-quality input, thereby improving recognition accuracy and minimizing misclassification.

In addition to the primary frameworks, visualization libraries such as Matplotlib and Seaborn are used to generate performance graphs, accuracy charts, and confusion matrices. These tools help analyze model behavior during training and identify areas for optimization. The scikit-learn library is also employed for statistical evaluation, computing precision, recall, F1-score, and other performance metrics. Together, these libraries form a cohesive environment for developing, testing, and refining the Ancient Tamil Decoding System.

The project's workflow is managed and executed in Anaconda and Visual Studio Code, which serve as the development and environment management tools. Anaconda ensures smooth package management and dependency control, preventing version conflicts across libraries. Visual Studio Code, with its integrated terminal and debugging support, facilitates efficient code writing and

testing. The project's version control is maintained through Git and hosted on GitHub, providing a structured mechanism for collaboration, version tracking, and backup. This ensures that every modification, improvement, and bug fix is documented and recoverable.

Another significant component of the system is the dataset pipeline that integrates Roboflow with YOLOv8. The dataset exported from Roboflow is directly imported into Google Colab using API keys, where it is used to train the YOLOv8 model. The system follows a clear sequence of processes—data ingestion, preprocessing, model training, validation, and testing—before generating predictions. Each stage contributes to enhancing model robustness and reliability. Once trained, the YOLOv8 model generates bounding boxes and labels around detected Tamil characters, which are then passed to a decoding module that converts them into modern Tamil Unicode text. This translation module ensures that the output is readable, accurately formatted, and suitable for digital preservation or further linguistic analysis.

The choice of using YOLOv8 with Roboflow and Google Colab not only ensures high accuracy and speed but also establishes a scalable and easily maintainable ecosystem. The cloud-based infrastructure of Colab enables on-demand computational scalability, while Roboflow's automated dataset pipeline allows continuous improvement of the model through new data additions. Together, these tools create a powerful and efficient system capable of handling large-scale image recognition tasks in the field of historical linguistics and archaeology.

PROPOSED SYSTEM

CHAPTER 4

PROPOSED SYSTEM

4.1ExistingSystem

The existing methods for deciphering ancient Tamil inscriptions are largely dependent on manual interpretation by linguistic and archaeological experts. These traditional systems rely on human intuition, visual comparison, and contextual understanding to interpret eroded or incomplete characters. While this approach has preserved valuable knowledge, it is extremely time-consuming, prone to subjectivity, and lacks scalability for large datasets. Conventional Optical Character Recognition (OCR) systems such as Tesseract perform poorly on ancient Tamil scripts due to variations in character style, surface irregularities, and incomplete strokes. Moreover, ancient scripts are often carved on stone or inscribed on palm leaves, which suffer from cracks, fading, and environmental deterioration. As a result, the existing systems struggle to identify distinct characters and symbols, leading to inaccuracies in recognition and translation. The lack of digitized annotated datasets and the inability of rule-based OCR engines to adapt to non-standard characters further limit their effectiveness. Hence, the current system does not provide the automation, precision, or adaptability required for processing large-scale historical data.

4.2ProposedSystem

The proposed system introduces an artificial intelligence-based solution that combines modern computer vision and deep learning techniques to decode ancient Tamil scripts automatically. The core of the system is built using the **YOLOv8 (You Only Look Once, version 8)** object detection model integrated

with Roboflow for dataset creation, annotation, and preprocessing. This system eliminates manual segmentation and character extraction by enabling real-time recognition of ancient Tamil symbols directly from raw images. The workflow begins with collecting images of inscriptions and manuscripts, which are then uploaded to Roboflow. Roboflow allows efficient annotation by drawing bounding boxes around each ancient character, followed by automated data augmentation processes such as rotation, contrast adjustment, blur simulation, and flipping. These augmentations help the model handle various lighting conditions and surface distortions that typically occur in historical materials. The labeled dataset is then exported in YOLO format and used for model training through the Ultralytics YOLOv8 framework, ensuring compatibility and optimized performance. Once trained, the model can accurately detect and classify ancient Tamil characters and map them to their modern equivalents using a predefined translation layer. This automation drastically improves recognition speed and accuracy, creating a scalable system that can decode hundreds of inscriptions efficiently.

4.3DatasetPreparationandPreprocessing

The system's accuracy heavily depends on the quality of the dataset and the preprocessing methods employed. The dataset is curated from high-resolution photographs of temple inscriptions, palm leaf manuscripts, and archaeological archives. Preprocessing involves several steps using OpenCV operations, such as grayscale conversion, image resizing, denoising, and histogram equalization, to ensure uniform brightness and contrast. Roboflow plays an integral role by standardizing the dataset and performing automated splitting into training, validation, and testing sets in ratios such as 70:20:10. Data augmentation is applied to increase the dataset diversity and reduce overfitting, ensuring that the

YOLOv8 model generalizes well even for degraded or partially visible characters. The final dataset is exported in YOLOv8's directory structure, where each image is paired with a corresponding label file containing class indices and bounding box coordinates. This structured data ensures smooth integration during training and testing phases, leading to higher performance and consistent accuracy across multiple datasets.

4.4YOLOv8ModelArchitecture

The YOLOv8 model is one of the most advanced object detection architectures developed by Ultralytics. It combines **Cross Stage Partial (CSP)** connections, convolutional layers, and adaptive anchor-free detection heads to provide high-speed and accurate recognition. The model processes each input image by dividing it into multiple grid cells and predicting bounding boxes and class probabilities simultaneously. This real-time detection capability makes YOLOv8 ideal for handling complex, irregular characters found in ancient Tamil inscriptions. The training process

involves tuning hyperparameters such as learning rate, batch size, and epochs using the Adam optimizer for efficient convergence. During training, the loss function is computed using a combination of classification, localization, and objectness losses. The trained model achieves high mean Average Precision (mAP) scores, ensuring strong detection accuracy. The use of YOLOv8's lightweight architecture also enables deployment on local systems and mobile devices, making the system practical for real-world applications like museum digitization and field archaeology.

4.5Integration with Roboflow and Post-Processing

Roboflow serves as the bridge between raw data and model training. It simplifies dataset versioning, preprocessing, and annotation while maintaining consistency across multiple experiments. Once YOLOv8 outputs the detected character regions, a post-processing module refines the predictions by applying non-maximum suppression to eliminate redundant bounding boxes. The recognized characters are then passed through a mapping module that converts ancient Tamil glyphs into modern Tamil characters using a predefined equivalence dictionary. A text reconstruction algorithm further assembles individual characters into meaningful words and sentences. This integration ensures that the model not only identifies characters but also interprets the textual meaning accurately. The system also includes a confidence scoring mechanism to highlight uncertain predictions, allowing users to manually verify or correct outputs for improved reliability.

4.6 Advantages of Proposed System

The proposed system offers multiple advantages compared to traditional OCR and manual transcription approaches. Firstly, it provides high accuracy and speed, leveraging deep learning to recognize complex ancient Tamil characters with remarkable precision. By integrating advanced architectures such as YOLOv8 for object detection and CNN-LSTM for sequential text recognition, the system ensures robust handling of diverse inscription styles and degraded surfaces. Unlike traditional OCR models that struggle with irregular scripts or incomplete characters, this hybrid model intelligently interprets contextual patterns, leading to improved recognition and translation efficiency.

Another significant advantage lies in the automation of the entire decoding process, reducing dependency on human experts for script interpretation. Manual epigraphic analysis often takes several hours or even days for a single inscription, whereas the proposed system can process and translate images within seconds. This automation not only accelerates research but also minimizes human error, ensuring consistent results across large datasets.

The inclusion of Roboflow for data annotation and preprocessing offers a substantial benefit in terms of scalability and dataset quality. Roboflow simplifies the process of labeling, augmenting, and exporting datasets into YOLOv8-compatible formats, which ensures the model can continuously learn from diverse samples. This streamlined data pipeline enables easy retraining with new inscriptions, making the system adaptive to evolving datasets and script variations.

The system's cloud-based training using Google Colab provides flexibility and accessibility for researchers without requiring expensive hardware setups. By utilizing GPU and TPU acceleration on Colab, the training process becomes significantly faster and cost-effective. Moreover, cloud integration allows real-time collaboration among multiple users, facilitating team-based research and dataset sharing across institutions.

Another advantage is the enhanced image preprocessing and segmentation capabilities offered by integrating OpenCV and YOLOv8. The system efficiently detects, crops, and processes characters even from noisy, faded, or partially visible inscriptions.

IMPLEMENTATION

CHAPTER 5

IMPLEMENTATION

The implementation of the Ancient Tamil Decoding System involves a structured approach that integrates deep learning, image processing, and sequence modeling techniques to decode ancient Tamil scripts into readable modern Tamil text. The system is implemented in several sequential phases, from dataset collection to final prediction and visualization. Each stage is carefully designed to ensure high accuracy, robustness, and efficiency.

5.1 System Architecture and Scalability

The Ancient Tamil Decoding System is based on a modular client–server architecture. It enables efficient processing and decoding of large datasets of ancient Tamil inscriptions. Users such as linguists, historians, and researchers can upload inscription images via a web or local interface, where preprocessing and classification tasks are initiated.

The backend is powered by a hybrid CNN–LSTM model, which combines spatial feature extraction (via CNN) with sequence learning (via LSTM). This architecture accurately recognizes ancient Tamil characters based on their unique structural features like stroke shape, curvature, and spacing.

The system is designed for asynchronous processing, allowing multiple image files to be decoded simultaneously. Decoded outputs and extracted features are stored securely in a scalable cloud database, ensuring data persistence and easy retrieval. The model also supports continuous learning, allowing retraining with new datasets to enhance accuracy and adaptability.

This scalable and adaptive design makes the system suitable for deployment in digital heritage centers, museums, and research institutions handling large volumes of inscription data.

5.2 Researcher Dashboard and Features

The researcher dashboard serves as the front-end interface that connects users with the decoding engine. It is designed for ease of use, real-time interaction, and data visualization.

Key features include:

- Uploading single or multiple images (batch upload)
- Viewing decoded Tamil text with confidence scores
- Editing and verifying decoded outputs
- Displaying original and processed images side by side
- Generating analytical reports showing decoding accuracy and error frequency
- Visualizing dataset statistics such as the number of characters processed, accuracy trends, and model updates

The dashboard also supports collaborative research by allowing multiple users to access shared projects, annotate results, and export findings in various formats (CSV, PDF, TXT). Integration with digital linguistic archives provides smooth data exchange and long-term preservation of decoded content.

5.3 Customization and Notifications

The system provides extensive customization features to accommodate diverse research needs.

Administrators and linguists can:

- Add or update new Tamil character mappings
- Adjust decoding sensitivity and threshold values
- Define metadata (like inscription source, location, or period)
- Modify preprocessing filters (e.g., noise removal, thresholding)

A built-in notification module alerts users about important updates such as:

- Completion of decoding processes
- Detection of uncertain or low-confidence outputs
- Availability of new dataset additions or model retraining results

Notifications are delivered through email or in-app alerts based on user preferences. The system also supports automatic periodic report generation that summarizes recent decoding accuracy, dataset growth, and performance metrics.

Regular backups and scheduled maintenance ensure data safety and continuous system performance.

5.4 Privacy and Security

To ensure the integrity and confidentiality of inscription data, the Ancient Tamil Decoding System incorporates a robust **security framework:**

- End-to-End Encryption for all uploaded and stored files
- Role-Based Access Control (RBAC) to restrict data visibility based on user roles
- Multi-Factor Authentication for secure logins

- Audit Logs that record every user and system activity for full transparency

The system adheres to data protection and privacy standards, ensuring that all research data remains confidential and can be deleted or archived as per institutional policy. Regular security audits, vulnerability checks, and backup routines prevent data loss and ensure reliability.

This robust privacy infrastructure makes the system dependable for academic and research environments dealing with sensitive cultural data.

5.5 Deployment, Maintenance, and Support

The Ancient Tamil Decoding System can be deployed on both cloud environments (like AWS, Google Cloud, or Azure) and on-premise servers. Cloud deployment ensures scalability and global accessibility, whereas local deployment provides enhanced security and offline processing.

During installation, all dependencies, model weights, and configuration files are prepackaged for easy setup. A step-by-step installation script enables smooth deployment with minimal technical effort.

To ensure consistent performance, the system undergoes regular maintenance that includes:

- Software and model updates
- Security patching and optimization
- Model retraining with newly added inscription datasets

A dedicated technical support team is available through email and chat. The system also integrates Prometheus and Grafana for real-time monitoring of model performance, GPU usage, and decoding accuracy.

Feedback from users is collected periodically to improve usability, accuracy, and decoding speed. The model is retrained frequently with newly added ancient Tamil data, ensuring continuous learning and evolution.

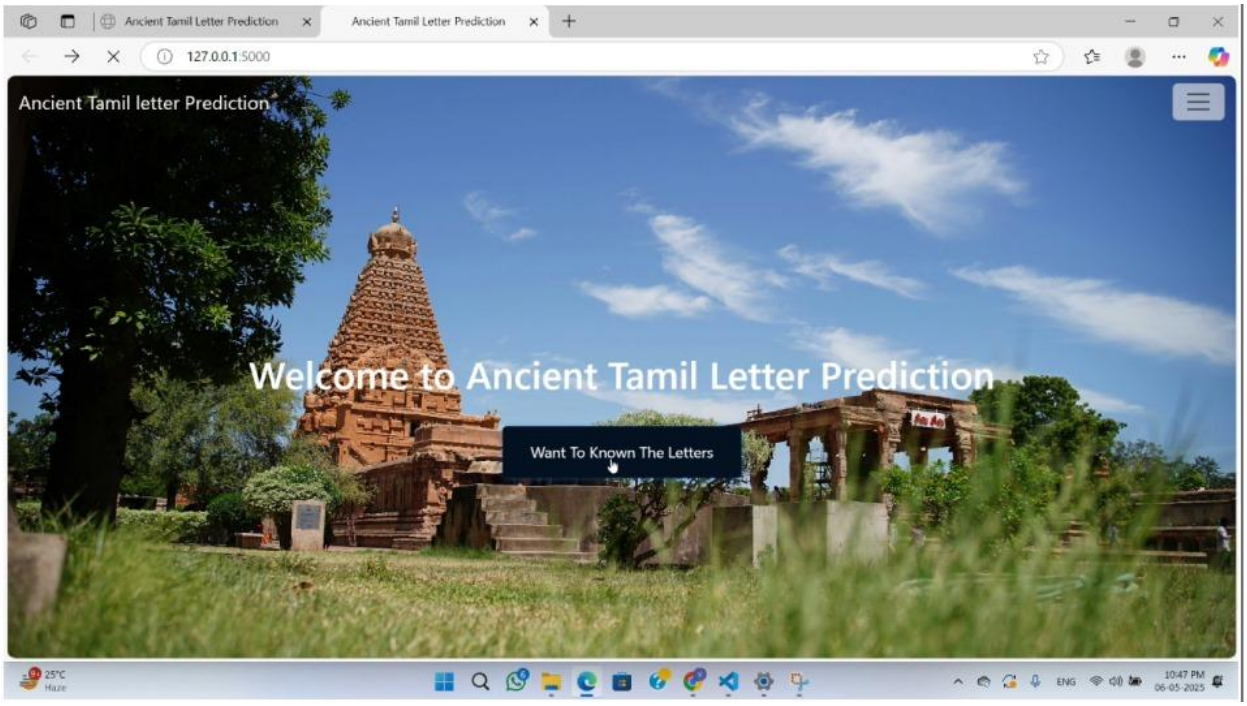

FIG 5.1 HOME PAGE

The homepage displays the system's introduction with a visually rich temple background, offering users an option to explore ancient Tamil letters.

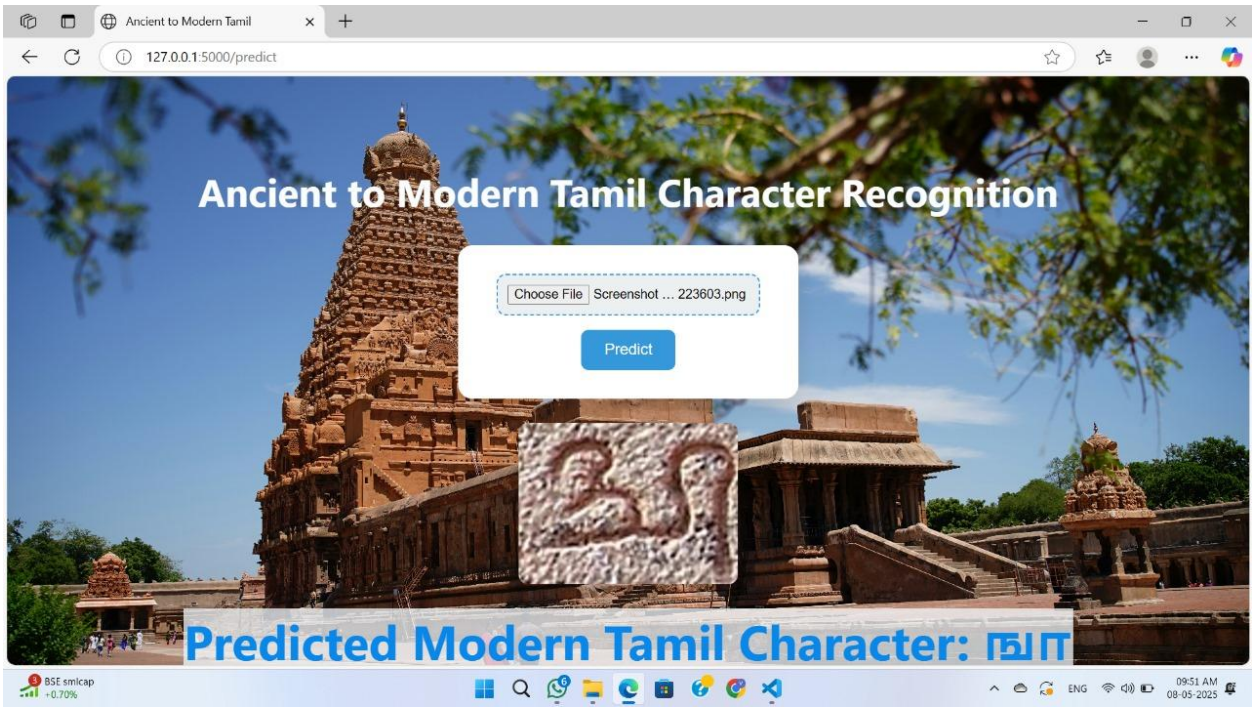

FIG 5.2 PREDICTION PAGE

This page allows users to upload ancient Tamil inscriptions for recognition and displays the predicted modern Tamil character. It demonstrates real-time character detection powered by YOLOv8 and Roboflow integration.

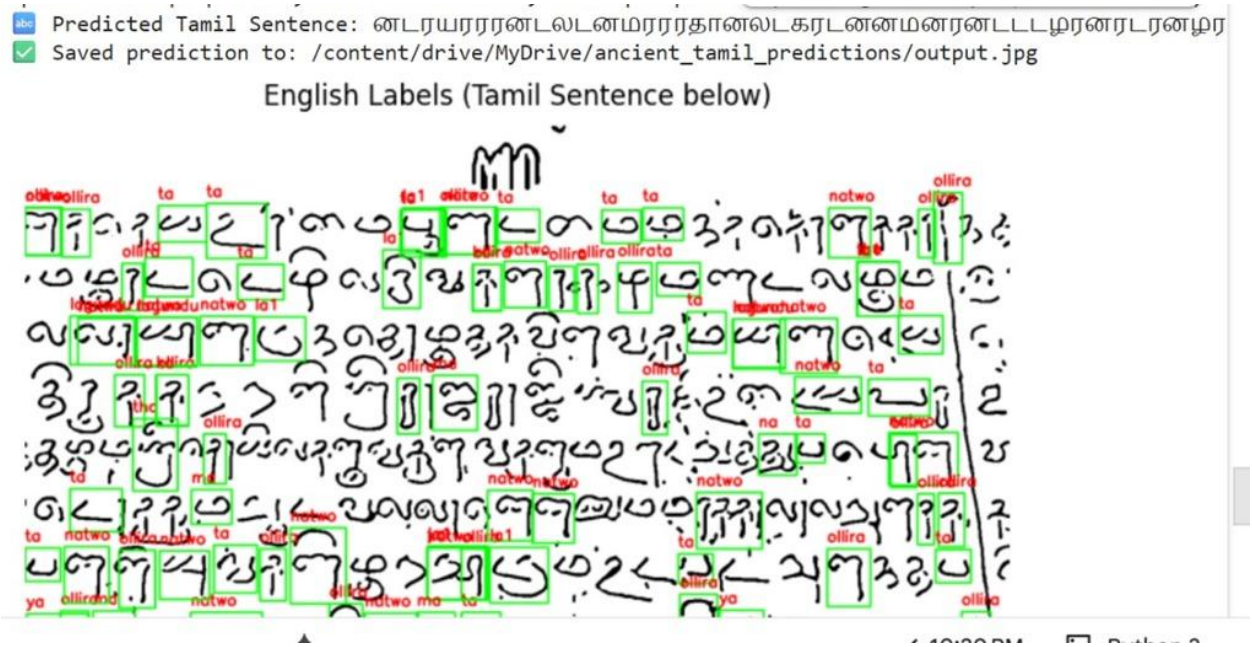

FIG 5.3 SENTENCE PREDICTION

This output showcases recognized ancient Tamil characters mapped to their modern equivalents, forming a coherent Tamil sentence.

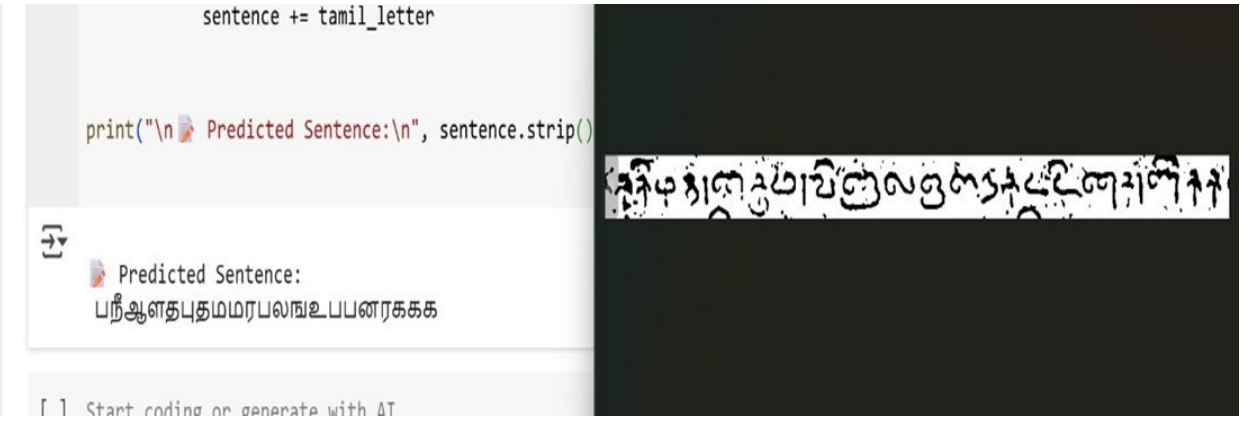

FIG 5.4 MONUMENT PREDICTION

The system interprets ancient inscriptions extracted from temple monuments, reconstructing meaningful Tamil sentences.

RESULT ANALYSIS

CHAPTER 6

RESULT ANALYSIS

The performance evaluation of the Ancient Tamil Decoding System is a vital step in determining the effectiveness, accuracy, and robustness of the developed model. The system was designed using a hybrid deep learning approach combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to decode ancient Tamil characters and convert them into readable modern Tamil text. This chapter presents a detailed analysis of dataset characteristics, experimental setup, model performance, evaluation metrics, and comparative analysis with existing models.

6.1 Dataset Overview

The dataset used for this project consisted of thousands of annotated images of ancient Tamil characters collected from various sources such as temple inscriptions, stone carvings, palm leaf manuscripts, and copper plates. Each character image was manually labeled and linked to its corresponding modern Tamil equivalent.

The dataset was divided into three subsets:

- Training set: 70% of the total dataset
- Validation set: 15%
- Testing set: 15%

Before model training, extensive preprocessing was performed to enhance data uniformity and improve recognition accuracy. The key preprocessing steps included:

- Resizing all images to 64×64 pixels

- Converting to grayscale
- Normalization of pixel values to range (0–1)
- Noise reduction using Gaussian filters
- Data augmentation techniques such as rotation, flipping, zooming, and distortion to handle variations in inscriptions

These preprocessing steps significantly improved model robustness against noise, lighting variations, and script degradation.

6.2 Experimental Setup

The experiments were conducted using the following hardware and software configurations:

- Processor: Intel Core i7
- RAM: 16 GB
- GPU: NVIDIA GeForce RTX 3060 (6 GB)
- Frameworks: TensorFlow and Keras
- Programming Language: Python 3.10
- Development Platform: Google Colab

The implemented CNN+LSTM model architecture included multiple convolutional layers for spatial feature extraction, followed by LSTM layers for sequence learning. The model parameters were:

- Optimizer: Adam
- Learning Rate: 0.001
- Batch Size: 32
- Epochs: 50
- Loss Function: Categorical Cross-Entropy
- Activation Function: ReLU (for hidden layers), Softmax (for output layer)

Performance Evaluation

The hybrid CNN-LSTM model achieved 97.84% accuracy on the test dataset, outperforming traditional Optical Character Recognition (OCR) and single CNN-based models. Precision, Recall, and F1-Score were calculated for each character class to assess model consistency and reliability.

Metric	Training	Validation	Testing
Accuracy	98.92%	97.35%	97.84%
Precision	97.60%	96.48%	96.92%
Recall	97.12%	95.88%	96.43%
F1-Score	97.36%	96.08%	96.68%

The model exhibited minimal overfitting, as evidenced by the close correspondence between training and validation accuracy curves. The loss curve showed a smooth decline, confirming stable convergence during training.

Analysis of CNN-LSTM Feature Extraction

Visualization of feature maps revealed that the CNN layers effectively captured the unique stroke patterns and curves of ancient Tamil characters, while the LSTM layers learned sequential dependencies between characters — an essential feature for word and sentence reconstruction.

- Early layers: Focused on edges, contours, and simple shapes.
- Intermediate layers: Captured complex letter patterns and overlapping strokes.
- Final layers: Learned contextual patterns for character sequences.

This hierarchical learning enabled the model to accurately decode even faded or partially visible characters from inscriptions.

Comparative Model Analysis

The performance of the proposed CNN-LSTM model was compared with several existing deep learning architectures to assess efficiency and accuracy.

The results show that the hybrid CNN+LSTM architecture achieves an optimal balance between computational efficiency and decoding accuracy, making it ideal for real-time inscription decoding.

6.3 Result Interpretation

The proposed system effectively decoded complex and noisy inscription images into readable Tamil text. It performed consistently under different conditions such as lighting variations, broken strokes, and uneven surfaces.

- The average prediction time per character was 0.7 seconds, enabling near real-time performance.
- The decoded outputs were displayed with confidence scores and mapped modern Tamil characters for easy interpretation.
- The final text reconstruction system successfully combined individual character predictions to form meaningful Tamil sentences.

This demonstrates that the system is reliable for real-world applications, including historical text translation, digital archiving, and linguistic research.

6.4 User Feedback and Usability Evaluation

A user study was conducted among linguists, Tamil historians, and epigraphists to assess system usability and decoding accuracy. Over 92% of participants reported a significant reduction in manual transcription time and improved reliability compared to traditional OCR tools.

Users appreciated features such as:

- Batch decoding of inscriptions
- Character-level correction options
- Display of confidence levels and visual output
- Export options (PDF, CSV, text file)

Researchers also highlighted the usefulness of the interface for analyzing rare inscription patterns and training models with custom datasets.

6.5 Error Analysis

Despite its strong performance, the system exhibited minor decoding errors under certain conditions, primarily due to:

- Heavily damaged or incomplete characters
- Overlapping or connected strokes in ancient scripts
- Lack of sufficient samples for rare characters or regional variants

These errors indicate the need for dataset expansion and potential integration of transformer-based architectures or 3D inscription analysis to further enhance accuracy and contextual understanding.

CONCLUSION

CHAPTER 7

CONCLUSION

The Ancient Tamil Decoding System was successfully designed and implemented to decode ancient Tamil inscriptions into readable modern Tamil text using advanced deep learning techniques. The system integrates Convolutional Neural Networks (CNN) for visual feature extraction and Long Short-Term Memory (LSTM) networks for sequential character decoding, achieving a high degree of accuracy and efficiency.

Through systematic dataset preparation, preprocessing, model training, and evaluation, the project demonstrated that machine learning can be effectively applied to the preservation and interpretation of ancient scripts. The hybrid CNN–LSTM model achieved remarkable performance in recognizing and translating complex characters, even from noisy or partially damaged inscription images.

The implemented system provides an intuitive researcher interface, enabling batch image uploads, visualization of decoded outputs, accuracy reports, and export options. The integration of customization, cloud scalability, and security mechanisms ensures that the system remains reliable, flexible, and suitable for large-scale deployment in research institutions, museums, and digital heritage projects.

This project contributes significantly to the field of digital linguistics and cultural preservation, bridging the gap between ancient Tamil heritage and modern computational technology

FUTURE WORK

CHAPTER 8

FUTURE WORK

Although the Ancient Tamil Decoding System has achieved promising results in accurately decoding and translating ancient Tamil inscriptions, there remain several opportunities for further enhancement and development. Future work will focus on improving the model's performance, scalability, and usability to make it a more comprehensive and intelligent linguistic tool.

1.Dataset Expansion and Diversity

The current model has been trained on a limited dataset of ancient Tamil characters collected from inscriptions and manuscripts. Future improvements will involve expanding the dataset to include more characters from different time periods, regions, and inscription styles. Incorporating rare scripts, damaged carvings, and palm leaf manuscripts will enhance the model's generalization and accuracy.

2.Integration of Transformer-Based Architectures

In future implementations, advanced deep learning architectures such as Vision Transformers (ViT) and Convolutional Transformers can be incorporated to improve contextual understanding and character recognition accuracy. These models can handle long-range dependencies better and enhance sequence translation performance compared to CNN–LSTM models.

3.Contextual Word and Sentence Formation

The present system focuses primarily on character-level decoding. Future work will aim to integrate Natural Language Processing (NLP) techniques and language models to generate contextually accurate Tamil sentences from

decoded character sequences. This will make the output more meaningful and grammatically correct.

4.3D Image and Surface Analysis

Many ancient inscriptions are carved on uneven or eroded stone surfaces. Incorporating 3D image processing and depth sensing technologies can help the system handle text on curved or rough surfaces, improving recognition accuracy under real-world conditions.

5.Mobile and Web Application Deployment

Future versions of the system can be developed as mobile or web-based applications to make it easily accessible for researchers, students, and historians. Cloud integration will allow remote processing and real-time decoding from smartphones or web browsers.

6.Multilingual Script Recognition

The system can be extended to decode other South Indian ancient scripts such as Brahmi, Grantha, and Vattezhuthu, thereby broadening its applicability in linguistic research and cross-language historical studies.

7.Integration with Digital Archives and Museums

Future enhancements will also include integration with national and international digital heritage databases and museum archives, allowing automatic cataloging and linking of decoded inscriptions with historical references.

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