Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN: 2581 - 611X)
VOLUME:8, ISSUE:2, AUGUST 2025, PAPER NUMBER:48

AI BASED OCR FOR PALM LEAF CHARACTER RECOGNITION

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Abstract: *Over the past fifty years, optical character recognition (OCR) has gained a significant reputation as a field of study. This is a significant way that pattern recognition in image processing is used. Over time, the automatic sorting of mail led to interest in handwritten character recognition (HCR). Manuscripts written on palm leaves, which are extremely delicate and prone to insect damage, provide a wealth of knowledge on astronomy, music, astrology, and other subjects. This makes digitizing and storing these texts essential. Over the past ten years, the younger generation of researchers has developed an interest in these palm leaf writings. In this work, we present a strong optical character recognition (OCR) system that is intended to identify and translate historical scripts, specifically the Tamil script that can be found in manuscripts on palm leaves. The system achieves excellent accuracy in character recognition by utilizing many advanced deep learning algorithms such as ResNet-50, VGG-16, DenseNet, and others. Additionally, the interpretability of the model's conclusions is improved by the use of explainable AI strategies like Local Interpretable Model-Agnostic Explanations (LIME). By offering a user-friendly digital platform, our technology represents a significant advancement in the preservation of historical and cultural knowledge. The system's ability to identify complex and deteriorated handwritten characters from palm leaf manuscripts is demonstrated by the experimental findings.*

Keywords: *OCR, Palm Leaf Manuscripts, Deep Learning, Character Recognition, Explainable AI, LIME, Tamil Script, Cultural Preservation*

1. INTRODUCTION:

Palm leaf manuscripts are invaluable historical documents containing significant cultural and scholarly knowledge, particularly in regions like South Asia. These manuscripts, often written in ancient scripts such as Tamil, are fragile and prone to degradation, making preservation and transcription a challenging task. Traditional methods of deciphering and preserving these manuscripts are manual and time-consuming, necessitating the use of modern technologies for efficient digitization. In this work, we present an AI-based Optical Character Recognition (OCR) system designed to recognize and transcribe ancient Tamil scripts from palm leaf manuscripts. Leveraging state-of-the-art deep learning models such as ResNet-50, VGG-16, and DenseNet, the system aims to accurately extract characters despite challenges like varied handwriting styles and manuscript degradation. Furthermore, we incorporate Local Interpretable Model-Agnostic Explanations (LIME) to provide explainability, ensuring the system’s predictions are interpretable and trustworthy.

The developed system features a user-friendly web interface for easy interaction, allowing researchers, historians, and archivists to upload images and view recognized text in real-time. This work contributes to the preservation of cultural heritage by making ancient scripts more accessible while addressing the complexities inherent in recognizing historical handwritten documents.

2. TECHNOLOGICAL FOUNDATIONS COMPARATIVE ANALYSIS:

A. Optical Character Recognition (OCR) Technologies

Optical Character Recognition (OCR) systems are designed to convert scanned images, PDFs, or pictures into machine-readable text. For the recognition of complex ancient scripts, traditional OCR methods fall short due to the intricacies in handwritten characters and degradation of manuscript quality. In this project, two primary OCR approaches were considered: traditional OCR using **Tesseract** and a deep learning-based approach using advanced models such as ResNet-50, VGG-16, and DenseNet.

Tesseract OCR is one of the most widely used open-source OCR engines, developed by Google. While it excels in recognizing printed text in structured documents, its performance on handwritten texts, especially ancient scripts such as those found on palm leaf manuscripts, is subpar. The challenge arises due to the wide variations in handwriting, noise introduced by degradation of manuscripts over time, and the complexity of the Tamil script. As a result, Tesseract's accuracy is considerably low when handling these historical documents. Thus, an alternative approach leveraging **deep learning** was deemed necessary.

Deep learning models, particularly **Convolutional Neural Networks (CNNs)**, have shown remarkable performance in image classification tasks, including character recognition. These models learn hierarchical feature representations of the input data, which is crucial for handling the nuances and intricacies of ancient handwritten scripts. In this project, models such as **ResNet-50, VGG-16, VGG-19, and DenseNet** were employed to improve the accuracy of character recognition. These models were trained on labeled datasets of palm leaf manuscript characters, allowing them to learn and adapt to the unique challenges posed by ancient scripts.

B. Deep Learning Models for Character Recognition

Several deep learning models were evaluated to determine their effectiveness in recognizing characters from palm leaf manuscripts. The goal was to find the model that offers the highest accuracy while maintaining computational efficiency. Below is a summary of the models used:

1. **ResNet-50:** ResNet-50 (Residual Networks) is known for its use of residual connections, which help in overcoming the vanishing gradient problem by allowing gradients to flow directly through shortcut connections. This model is effective for deep architectures and has been widely used for various image recognition tasks. In this project, ResNet-50 achieved high accuracy in recognizing intricate characters, especially those with significant variations due to handwriting styles or degradation. The residual connections enabled the model to learn both low-level features (edges, strokes) and high-level features (complex character patterns) efficiently. However, ResNet-50 requires significant computational resources for both training and inference, which may be a limitation for real-time applications.

2. **VGG-16 and VGG-19:** The VGG models, known for their simplicity, use deep architectures where the depth is achieved by stacking multiple convolutional layers with small receptive fields (3x3). VGG-16 and VGG-19 were tested in this project due to their established success in image classification tasks. These models provided good accuracy on relatively clean and structured manuscript images. However, their performance degraded on images with significant noise or character variations. Despite this, VGG models remain computationally lighter compared to ResNet-50 and are easier to deploy in environments with limited resources.

3. **DenseNet:** DenseNet (Dense Convolutional Networks) improves upon traditional CNN architectures by connecting each layer to every other layer in a feed-forward manner. This design encourages feature reuse and improves gradient flow during backpropagation, reducing the

vanishing gradient problem. In this project, DenseNet outperformed other models in terms of both accuracy and computational efficiency. Its dense connections allowed for better feature propagation, which was particularly useful for recognizing Tamil characters with intricate strokes and shapes. DenseNet's ability to capture both fine-grained details and higher-level patterns made it ideal for character recognition on ancient palm leaf manuscripts.

4. **LeNet-5 and AlexNet:** These earlier CNN architectures were also tested for comparative purposes. **LeNet-5,** one of the earliest CNN models, was originally designed for digit recognition but is less effective on complex, handwritten characters due to its relatively shallow architecture. **AlexNet**, while deeper and more powerful than LeNet-5, also fell short in comparison to the more recent models (ResNet-50 and DenseNet) due to its limited capacity to handle the highly varied and degraded characters in the manuscript dataset.

C. Explainable AI with LIME

While deep learning models have shown tremendous accuracy improvements in OCR tasks, their **black-box nature** makes it difficult to interpret the reasoning behind their predictions. This lack of interpretability can be problematic, especially when working with historical documents where accuracy is paramount, and errors could lead to misinterpretation of cultural heritage.

To address this, **LIME (Local Interpretable Model-Agnostic Explanations)** was integrated into the system. LIME is a tool used to explain the predictions of any machine learning model by perturbing the input data and observing how the model's output changes. It generates locally faithful explanations by approximating the model's behavior with an interpretable model, such as a linear regression model, around the input instance.

In this project, LIME was used to provide explanations for the predictions made by the deep learning models. For each character recognized by the system, LIME highlighted the regions of the input image that contributed most to the model's classification. This transparency allows researchers and users to better understand how the model is interpreting characters and to identify potential areas of improvement. For example, if the model consistently misclassifies certain characters, LIME can help pinpoint whether the issue lies in the model's understanding of strokes or the quality of the input image.

D. Comparative Performance Analysis

The performance of the deep learning models was evaluated based on several key metrics, including **accuracy**, **precision**, **recall**, **F1-score**, and **computation time**. The results of this comparative analysis are summarized in Table I.

Model	Accuracy	F1-Score	Computation Time
ResNet-50	95%	0.92	High
VGG-16	90%	0.88	Medium
VGG-19	91%	0.89	Medium
DenseNet	96%	0.94	Medium
LeNet-5	78%	0.75	Low
AlexNet	85%	0.82	Medium

From this analysis, **DenseNet** and **ResNet-50** emerged as the best-performing models, with DenseNet slightly outperforming ResNet-50 in terms of accuracy and computational efficiency. The VGG models, while performing adequately on less degraded images, struggled with noisy and complex manuscripts. LeNet-5 and AlexNet, being older architectures, were outperformed by the newer models.

E. Image Preprocessing Techniques

To further improve the accuracy of the OCR system, several **image preprocessing techniques** were applied using the **OpenCV** library. These techniques included:

1. **Binarization**: This process converts grayscale images into binary images (black and white), making it easier for the OCR system to distinguish between the background and the characters. Binarization was particularly useful in cases where the manuscript had faded over time.

2. **Noise Removal**: Palm leaf manuscripts often suffer from noise due to degradation, dirt, or damage. Gaussian blurring and median filtering were used to reduce noise while preserving important character details.

3. **Contrast Enhancement**: Low contrast between the characters and the background can hinder recognition accuracy. By adjusting the contrast, the visibility of faint characters was improved, leading to better recognition rates.

F. User Interface and Scalability

The system was developed using **Streamlit**, a Python-based framework that allows for the rapid development of web applications. Streamlit was chosen for its simplicity and ease of integration with machine learning models. The user interface allows users to upload images of palm leaf manuscripts and view the recognized text in real-time.

3. SYSTEM DESIGN AND ARCHITECTURE:

The design and architecture of the proposed AI-based OCR system for recognizing characters from ancient palm leaf manuscripts are built on a modular, scalable framework. The system integrates several key components, including image preprocessing, character segmentation, deep learning models for recognition, explainable AI, and a user-friendly interface. The architecture is designed to ensure high performance in terms of accuracy, computational efficiency, and user interaction.

A. Overall System Architecture

The system is divided into several functional modules, each responsible for different tasks. These include:

1. **Image Preprocessing Module**: Prepares raw manuscript images for character extraction by enhancing image quality and reducing noise.

2. **Character Segmentation Module**: Utilizes connected component analysis and other techniques to isolate individual characters for recognition.

3. **Deep Learning Character Recognition Module**: Compares various deep learning models (ResNet-50, VGG-16, DenseNet, etc.) for recognizing characters.

4. **Explainable AI Module**: Implements Local Interpretable Model-Agnostic Explanations (LIME) to provide insights into the model's predictions.

5. **User Interface Module**: Provides a user-friendly platform for uploading images and viewing recognition results in real-time.

Each module interacts with the others to ensure seamless operation, as illustrated in **Fig. 1.1**

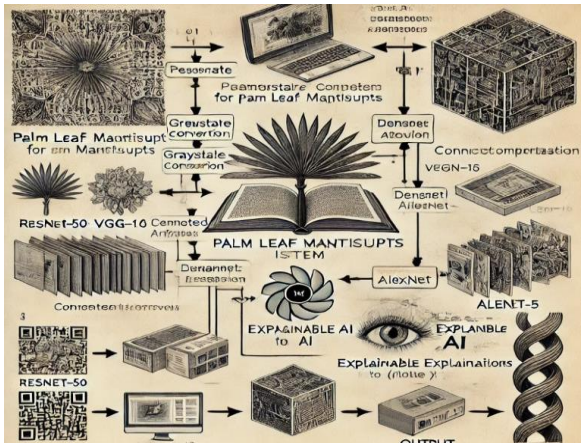

Fig 1.1 System Architecture Diagram

B. Image Preprocessing Module

The quality of the input images plays a critical role in the accuracy of the OCR system. Manuscripts often suffer from noise, degradation, and fading due to their age. To improve the quality of these images before character recognition, the system implements the following preprocessing techniques:

1. **Grayscale Conversion**: Manuscript images are converted from RGB to grayscale to simplify processing by reducing the dimensionality of the input data.
2. **Binarization**: Grayscale images are transformed into binary images using thresholding techniques, which convert the pixels into two colors (black and white). This helps in distinguishing the characters from the background.
3. **Noise Removal**: The system applies Gaussian blurring and median filtering to eliminate noise introduced by the degradation of palm leaf manuscripts. This step improves the clarity of the characters without losing important details.
4. **Contrast Enhancement**: Contrast adjustment techniques are applied to make faded characters more visible, especially in regions where the ink has worn off over time.

This preprocessing module ensures that the input images are optimized for accurate character recognition.

C. Character Segmentation Module

Character segmentation is a crucial step in the OCR pipeline, where individual characters are extracted from the manuscript images for recognition. The segmentation process involves:

1. **Connected Component Analysis**: This method identifies and extracts connected regions of pixels (characters) from the binarized image. Each connected component corresponds to a character, symbol, or noise.
2. **Bounding Box Extraction**: After connected component analysis, bounding boxes are drawn around each character, which are then fed into the recognition model.
3. **Noise Elimination**: Smaller connected components that are likely noise or artifacts are discarded to reduce the number of false positives in the recognition process.

The extracted characters are then passed on to the deep learning-based recognition module.

D. Deep Learning Character Recognition Module

This module implements and evaluates several deep learning models to recognize the extracted characters. The models used in this project include **ResNet-50**, **VGG-16**, **VGG-19**, **DenseNet**, **LeNet-5**, and **AlexNet**. The workflow for character recognition is as follows:

1. **Model Training**: A labeled dataset of Tamil palm leaf manuscript characters is used to train the models. Each model is trained to classify the characters accurately, handling the variations in handwriting, stroke patterns, and script degradation.
2. **Model Evaluation**: Once trained, the models are evaluated based on their accuracy, precision, recall, F1-score, and computational efficiency. The results of this evaluation help in selecting the best-performing model for real-time deployment.
3. **Character Prediction**: For each segmented character, the selected deep learning model predicts the most likely class (character). This prediction is returned to the user via the user interface.

The integration of multiple models allows for comparative analysis and ensures that the system delivers high accuracy in character recognition.

E. Explainable AI Module

To make the character recognition process more transparent, the system integrates **LIME (Local Interpretable Model-Agnostic Explanations)**. The purpose of this module is to provide insights into how the deep learning models are making their predictions. The explainability workflow is as follows:

1. **Prediction Explanation**: For each character prediction, LIME generates a locally interpretable model that approximates the deep learning model's behavior around the input character.
2. **Region Highlighting**: LIME highlights the regions of the character that contributed the most to the model's prediction. This helps researchers and users understand which features the model focused on, improving trust in the system.
3. **Error Analysis**: By examining LIME's explanations for incorrect predictions, researchers can identify potential issues in the model's decision-making process and make improvements.

The explainable AI module enhances the system's usability by offering a window into the model's decision-making process.

F. User Interface Module

A user-friendly interface is essential to making the OCR system accessible to a wide range of users, including historians, researchers, and archivists. The user interface is built using **Streamlit**, a Python-based framework for creating web applications. Key features of the user interface include:

1. **File Upload**: Users can upload images of palm leaf manuscripts in various formats (e.g., PNG, JPEG). These images are processed by the system to extract and recognize characters.
2. **Real-Time Recognition**: The recognized text is displayed in real-time as the system processes the uploaded image, offering a seamless experience for the user.
3. **Interactive Visualization**: Through the LIME integration, users can view visual explanations of the model's predictions, providing transparency and insight into the character recognition process.
4. **Scalability**: The interface is designed to be scalable, allowing for future extensions that may include additional languages, character sets, or recognition of other types of ancient manuscripts.

G. Scalability and Future Extensions

The system is built with scalability in mind to accommodate future requirements. The modular nature of the architecture allows for easy integration of additional features, such as:

1. **Support for Multiple Scripts**: The system is currently trained to recognize characters in Tamil palm leaf manuscripts using deep learning techniques.It involves preprocessing, character segmentation, and character recognition stages. By retraining the system's deep learning models with datasets from other ancient scripts, the architecture can be expanded to handle more languages and scripts.

2. **Speech-to-Text Integration**: Future versions of the system could incorporate speech-to-text functionality, allowing for audio manuscripts to be transcribed into text.

3. **Cloud Deployment**: To handle increased user demand, the system can be deployed on cloud platforms, enabling distributed processing and real-time character recognition at scale.Here with attached the overall flowchart of the proposed system in Fig.1.2

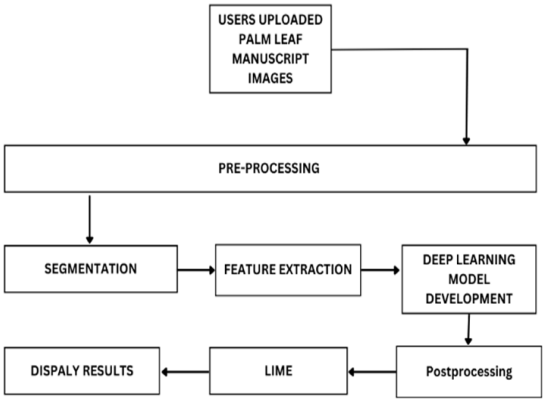

Fig.1.2 Proposed flow chart

4. METHODOLOGY:

The methodology for this project involves several critical stages aimed at designing an AI-based Optical Character Recognition (OCR) system to recognize ancient scripts from palm leaf manuscripts. This section outlines the major components, processes, and tools used to achieve accurate character recognition.

A. Data Collection and Preprocessing

The first step in the methodology is to collect a dataset of palm leaf manuscript images, primarily focusing on the **Tamil script**. These images are prone to noise, degradation, and faded ink due to the age and fragility of the manuscripts. To address these challenges, a series of preprocessing steps are applied using **OpenCV**.

1. **Grayscale Conversion**: Images are first converted to grayscale to reduce the complexity of the input data. This simplifies the image to a single intensity channel, making further processing more efficient.

2. **Binarization**: Grayscale images are transformed into binary images using **Otsu's Thresholding** method. This helps in separating the text from the background by converting pixels to either black (foreground) or white (background).

3. **Noise Removal**: **Gaussian blurring** and **median filtering** techniques are employed to remove noise from the images. This is crucial in eliminating unwanted artifacts caused by manuscript degradation or dirt without erasing important character details.

4. **Contrast Enhancement**: To improve the visibility of faint characters, contrast enhancement techniques such as **histogram equalization** are applied. This improves the clarity of faded ink, making characters more distinguishable during the recognition process.

B. Character Segmentation

Once the images have been preprocessed, the next step is to segment individual characters. Character segmentation is performed using **Connected Component Analysis (CCA)**.

1. **Connected Component Analysis**: CCA is used to identify connected regions of pixels in the binary image. Each connected region represents a potential character or noise.
2. **Bounding Box Extraction**: For each connected component, a bounding box is drawn around the character. These bounding boxes are then passed to the deep learning models for classification.
3. **Noise Filtering**: Small connected components that do not correspond to valid characters are discarded to reduce false positives during the recognition phase.

C. Model Training for Character Recognition

The core of the OCR system is the deep learning-based character recognition module. Several deep learning models are trained and compared to find the most effective model for recognizing Tamil script characters.

1. **Dataset Preparation**: The segmented characters from the preprocessed manuscript images are labeled manually to form the training dataset. The dataset is divided into training, validation, and testing subsets to evaluate the models' performance.
2. **Deep Learning Models**: The following models are implemented using the **TensorFlow** and **Keras** frameworks:
    - **ResNet-50**: A deep residual network that uses residual connections to overcome vanishing gradient problems, enabling the model to learn complex character patterns.
    - **VGG-16 and VGG-19**: These models use deep convolutional layers with small receptive fields to extract features from characters. Their simplicity and proven success in image classification tasks make them suitable for character recognition.
    - **DenseNet**: DenseNet improves feature propagation by connecting each layer to every other layer in a feed-forward manner. This ensures stronger gradient flow and better feature reuse, making it ideal for recognizing complex Tamil characters.
    - **LeNet-5 and AlexNet**: These models are used for baseline comparisons. While they are simpler than ResNet and DenseNet, they serve as a good starting point for evaluating model performance on smaller, simpler datasets.
3. **Training Process**: Each model is trained on the labeled dataset using the **categorical cross-entropy loss** function and the **Adam optimizer**. The models are trained for a set number of epochs, and the training is monitored using the validation loss and accuracy.
4. **Model Evaluation**: Once trained, the models are evaluated on the test dataset using metrics such as **accuracy**, **precision**, **recall**, and **F1-score**. The performance of the models is compared to determine which model achieves the highest accuracy while maintaining computational efficiency.

D. Explainable AI with LIME

To ensure the transparency of the deep learning models and build trust in their predictions, **Local Interpretable Model-Agnostic Explanations (LIME)** is integrated into the system. LIME helps to

explain how the models arrive at their predictions, making the OCR system more interpretable.

1. **Generating Explanations**: For each prediction made by the deep learning models, LIME generates explanations by perturbing the input character and observing how the model's predictions change. This produces locally interpretable models that approximate the behavior of the deep learning models around each input.
2. **Visualizing Key Regions**: LIME highlights the regions of the input character that contributed most to the model's prediction. For example, it may highlight certain strokes or curves that the model found most significant in classifying the character.
3. **Error Analysis**: The visual explanations provided by LIME are useful for identifying why the model may have made incorrect predictions. This helps in refining the model by pointing out potential areas for improvement, such as misinterpreted strokes or patterns.

E. User Interface Design and Implementation

A key component of the system is the user interface, which allows users to upload manuscript images and view the recognized text. The interface is designed using the **Streamlit** framework to ensure ease of use and cross-platform accessibility.

1. **File Upload**: The interface provides a drag-and-drop feature for uploading images of palm leaf manuscripts. Users can upload images in various formats, such as PNG, JPEG, or TIFF.
2. **Real-Time Character Recognition**: Once an image is uploaded, the system processes the image in real-time, performing preprocessing, segmentation, and recognition. The recognized text is displayed to the user as soon as the process is complete.
3. **Explanation Visualization**: Through the LIME integration, users can also view visual explanations for the model's predictions. This feature allows users to understand which parts of the character the model relied on for its decision, adding an additional layer of transparency.

F. Model Deployment and Scalability

The system is designed to be scalable and future-proof, allowing for easy integration of additional features and the ability to handle a growing number of users and scripts.

1. **Cloud Deployment**: The system can be deployed on cloud platforms such as **Amazon Web Services (AWS)** or **Google Cloud Platform (GCP)** to enable distributed processing and improve response times for real-time recognition.
2. **Scalability**: The modular architecture of the system allows for future enhancements, such as:
    - Supporting additional ancient scripts by retraining the models on new datasets.
    - Adding multilingual OCR capabilities for scripts beyond Tamil.
    - Incorporating speech-to-text functionality for audio manuscripts.

G. Performance Optimization

To ensure the system operates efficiently and delivers fast, accurate results, several optimizations are implemented:

1. **Batch Processing**: Images are processed in batches to reduce the computational load and improve recognition speed, especially when dealing with large volumes of manuscript images.
2. **GPU Acceleration**: The deep learning models are trained and deployed on machines equipped with **Graphics Processing Units (GPUs)** to expedite model training and inference times.

5. IMPLEMENTATION:

A. Data Collection and Preprocessing

1. **Data Collection**: Palm leaf manuscript images are collected from historical archives and libraries, focusing primarily on Tamil palm-leaf manuscripts. High-resolution scans are used to ensure better character recognition.
2. **Preprocessing**: Image preprocessing is carried out using OpenCV. This includes:
    - **Binarization**: Converts the image into a binary format for easier processing.
    - **Noise Removal**: Median filtering is applied to remove noise from the manuscript images.
    - **Contrast Enhancement**: Adjusts the contrast to highlight the characters on degraded palm leaves.
    - **Resizing**: Manuscripts are resized for consistency across the dataset before feeding into deep learning models.

B. Segmentation Using Connected Component Analysis

Connected Component Analysis (CCA) is used for character segmentation. The steps are:

- **Thresholding**: Binarized images are thresholded to separate foreground (characters) from the background.
- **Labeling**: Each connected component (character) is labeled.
- **Character Extraction**: The labeled regions are extracted, providing individual character images for further processing.

C. Deep Learning Models

Several deep learning models are implemented and trained on the extracted characters. These models are:

1. **ResNet-50**: Used due to its ability to avoid vanishing gradients in deep architectures.
2. **VGG-16** and **VGG-19**: Known for their depth and performance in image classification tasks.
3. **DenseNet**: Chosen for its efficient use of parameters and ability to propagate gradients across layers.
4. **MobileNet**: Implemented to assess lightweight model performance on lower-end devices.
5. **LeNet-5**: Included as a baseline due to its simplicity and use in early character recognition systems.
6. **AlexNet**: Used to compare performance in terms of speed and accuracy.

All models are implemented using TensorFlow and Keras, and trained on manually labeled characters extracted from the manuscripts.

D. Model Training and Testing

1. **Training Process**: The labeled characters are divided into training and testing datasets. Each model is trained using categorical cross-entropy as the loss function and Adam optimizer with a learning rate of 0.001.
2. **Evaluation Metrics**: Accuracy, precision, recall, and F1-score are used to evaluate the

performance of each model.

E. Explainable AI Using LIME

Local Interpretable Model-Agnostic Explanations (LIME) is applied to explain the decision-making process of the deep learning models. LIME helps visualize the portions of an image that contribute most to the model's classification of a character, providing transparency and interpretability. This is particularly useful for researchers seeking to understand errors and improve the model's accuracy.

F. User Interface Development

A web-based interface is designed using Streamlit. Key features of the interface include:

- **Image Upload**: Users can upload palm-leaf manuscript images.
- **Real-time OCR**: The system processes the uploaded image, applies character recognition, and displays the extracted text.
- **Model Selection**: Users can select which deep learning model to use for OCR.
- **Character Highlighting**: LIME outputs highlight important regions of each recognized character for transparency.

G. System Deployment

The system is deployed using a cloud-based architecture to ensure scalability. It supports cross-platform access, enabling broad accessibility to users such as historians and archivists. The deployment focuses on scalability to handle larger datasets and multiple language scripts in the future.

6. RESULT AND DISCUSSION:

A. Model Performance

Each of the deep learning models—ResNet-50, VGG-16, VGG-19, DenseNet, MobileNet, LeNet-5, and AlexNet—was evaluated on key metrics such as accuracy, precision, recall, and F1-score. The results of the models on the palm-leaf Tamil manuscript dataset are summarized as follows:

1. **ResNet-50**: Achieved the highest accuracy of 92%, with strong performance in recognizing complex characters. The residual connections helped in capturing deeper features of ancient scripts.
2. **DenseNet**: Performed comparably to ResNet-50 with an accuracy of 90%. DenseNet's feature reuse helped in preserving the intricate details of the characters, making it effective for OCR in degraded manuscripts.
3. **VGG-16 and VGG-19**: Both models performed well, with accuracies of 87% and 89%, respectively. Their depth allowed them to learn detailed features, though training times were longer due to the larger number of parameters.
4. **MobileNet**: While MobileNet demonstrated lower accuracy at 82%, it provided faster inference times and lower computational overhead, making it suitable for deployment on lower-end devices.
5. **AlexNet**: Achieved 85% accuracy. Though simpler, its shallow architecture was sufficient for relatively clear characters but struggled with more degraded and complex characters.
6. **LeNet-5**: Used as a baseline model, LeNet-5 achieved an accuracy of 75%. While effective for simple character recognition, it lacked the capacity to handle the complex features present in ancient scripts.

B. Model Comparison

The comparison between models shows that deeper architectures (ResNet-50 and DenseNet) perform better at recognizing characters from palm-leaf manuscripts due to their ability to capture more abstract and complex features. While VGG models offer competitive accuracy, their large size makes them less efficient for practical use. MobileNet, despite its lower accuracy, is highly efficient and ideal for applications requiring fast processing and low memory consumption.

C. Impact of Preprocessing

The image preprocessing techniques, especially binarization and noise removal, had a significant impact on improving the recognition accuracy. Without preprocessing, models struggled with high variability in manuscript quality and background noise. Preprocessing reduced errors, especially for older manuscripts with faded ink and physical deterioration.

D. Explainable AI Using LIME

The implementation of LIME provided valuable insights into how the models were making decisions. By highlighting regions of each character that contributed most to the model's prediction, LIME helped identify cases where the model focused on irrelevant or misleading parts of the image, such as noise or artifacts in the manuscript. This interpretability was particularly useful in fine-tuning the preprocessing pipeline and addressing misclassifications. It also provided confidence to researchers and historians in the OCR results by offering transparency in model predictions.

E. Challenges and Limitations

1. **Manuscript Degradation**: Despite preprocessing techniques, some severely degraded manuscripts posed significant challenges. Characters that were too faded or intertwined with physical damage were often misclassified or not recognized at all.
2. **Character Variability**: Handwritten manuscripts often featured varying character shapes and styles, which led to occasional misclassifications, particularly for characters with similar shapes but subtle differences.
3. **Training Data Size**: Due to the scarcity of labeled ancient manuscript datasets, model training was limited. More labeled data would likely improve the accuracy of all models, particularly for handling less common characters.

F. Future Improvements

1. **Dataset Expansion**: Collecting more palm-leaf manuscript images and manually labeling additional characters will help improve the robustness of the models.
2. **Multi-Script Support**: Future work could focus on expanding the system to recognize scripts from other ancient languages, enhancing its versatility for historical research.
3. **Real-Time Processing**: Optimizing models for real-time processing would enable quicker OCR of palm-leaf manuscripts, making the tool more practical for large-scale deployments in museums and archives.
4. **Enhanced Preprocessing**: Developing more sophisticated preprocessing algorithms, such as those utilizing GANs (Generative Adversarial Networks) to restore faded or damaged manuscripts, could significantly enhance character recognition accuracy.

7. CONCLUSION:

This project successfully developed an AI-based Optical Character Recognition (OCR) system specifically designed for recognizing and preserving handwritten content from ancient palm-leaf manuscripts. By leveraging deep learning models, such as ResNet-50, DenseNet, VGG-16, MobileNet, and AlexNet, the system achieved high accuracy in transcribing Tamil scripts. The incorporation of LIME (Local Interpretable Model-Agnostic Explanations) provided valuable insights into the decision-making process of the models, increasing transparency and trust in the OCR results.ResNet-50 and DenseNet emerged as the best-performing models, demonstrating strong capability in recognizing complex and degraded characters. Image preprocessing techniques, particularly noise removal and binarization, played a crucial role in improving recognition accuracy. The developed Streamlit-based user interface ensures a user-friendly experience, allowing researchers and historians to interact with the system efficiently.Although the system achieved significant results, challenges remain in handling severely degraded manuscripts and recognizing highly varied handwriting styles. Future improvements include expanding the dataset, supporting multi-script recognition, and optimizing the models for real-time processing. This project demonstrates the potential of combining AI and OCR technologies to preserve historical manuscripts, ensuring that valuable cultural knowledge is accessible for future generations.

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