

## **RECOGNIZING TAMIL CHARACTERS IN PALM LEAF MANUSCRIPTS (DEEP LEARNING)**

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ORCHID ID: 0009-0006-5721-0393

### **ABSTRACT**

Tamil is an ancient language that has a vast collection of literature written on palm leaves and other materials. Palm leaf manuscripts have been used as a versatile medium to record information on medicine, literature, theatre, and other subjects. Despite the need for digitization and transcription, recognizing cursive characters in palm leaf manuscripts remains a challenging task. This study introduces a novel Convolutional Neural Network (CNN) technique to train the characteristics of palm leaf characters, enabling CNN to significantly classify palm leaf characters during the training phase. Preprocessing of the input image is done using morphological operations to remove noise. Connected component analysis is a technique used in image processing to identify and label the individual connected regions, or components, in a binary image. Connected component Analysis is then used to segment the palm leaf characters, with feature processing including text line spacing, spacing without obstacle, and spacing with an obstacle. Finally, the extracted cursive characters are input into the CNN technique for final classification. Experiments are conducted using collected cursive Tamil palm leaf manuscripts to validate the performance of the proposed CNN with existing deep learning techniques in terms of accuracy, precision, recall, etc.

### **1. Introduction**

Tamil is a language with a rich literary heritage and is recognized as one of the oldest in the world. In ancient times, poets used Palm leaves, particularly in Tamil Nadu, to conceal information. The ancient literature includes masterpieces, such as Sangam literature, Vaishnava, Saiva, medicinal works, gastronomy, astrology, Vaastu, gems, music, dance, and theatre, as well as Siddha. There has been growing interest among academics in the past decade to preserve ancient medical texts in Tamil and their value. To preserve medical materials, numerous scholars have generated conserved old medical writings in Tamil, such as those by saints like Agathiyar, which have undergone the first phase of a digitalization process. Nearly 10,000 manuscripts have been successfully scanned. For digitizing historical documents, apps that identify handwritten characters have used three key methods: statistical, structural or syntactic, and neural network-based techniques

### **2.Literaturereview**

Ali and Joseph [8] developed a CNN perfect for dispensing real-time input pictures including Malayalam characters and the job of segmenting words and typescripts from an image and attractiveness prediction using the CNN model. The feature extraction job in this model is done implicitly in CNN by the gradient descent technique. This technique is efficiently utilized for digitizing Malayalam script, which comprises 36 consonants and 13 vowels, is approved out in stages, and has obtained an accuracy of 97.26 percent for the training dataset.

According to Narenthiran and Ravichandran [13], several knowledge systems were recorded in ancient India utilising palm leaf scrolls. The wisdom was mostly expressed in several characters of the ancient Sanskrit language.

Traditional knowledge, in accordance with Devika and Vijayakumar [12], aids in establishing lasting relationships between people and nature. This study aimed to distinguish between the contents of palm leaf documents that can be digitised, the specifics for digitization, and the various methods of palm leaf document scanning

### 3. Proposed Methodology

#### 1. Dataset:

The cursive Tamil palm leaf manuscripts are collected from the online images and stored in the database to document the target characters. In total, 100 images of cursive palm leaf texts are collected. Each bundle of leaves is usually tied together with cord threads through two holes pierced through the entire manuscript by the insertion of bamboo strips. The resultant bundle is completed by adding the heavy wooden covers on either side of the leaves, also tied by the cords or wrapped with a soft textile cloth.

#### 2.1 Background normalization / Background removal:

Pre-processing using background removal and Morphological operations

Historical documents typically encounter two types of issues. The first problem arises when the original document is in a state of decay or deterioration, and the second issue occurs when the document is converted into a digital format and has an uneven background. However, there are enhancement techniques available that can help to improve the quality of the image, particularly for low-contrast images. These techniques are effective in reducing uneven backgrounds and can facilitate the extraction of text from historical documents.

The process of pre-enhancement is applied to an input image  $I$  by using a linear function that stretches the image's grey level to its full dynamic range through contrast stretching. The output of this pre-enhancement process is depicted in the figure. The brightness of the input image is modified through this process, resulting in the increased distinction between the textual pixels and the background, which helps restore slightly faded text sections. Pre-processing transforms brighter pixels into even brighter ones, which may increase noise slightly, but it is necessary for preserving slightly faded text in both DIBCO and palm leaf documents. The proposed method effectively removes additional noise that may arise due to this change. The enhanced image  $IE$  is utilized to calculate the gradient image  $Gd$  in subsequent steps.

[Start] --> [Input Image  $I$ ] --> [Pre-enhancement using contrast stretching] --> [Enhanced Image  $IE$ ] --> [Calculate Gradient Image  $Gd$ ] --> [Noise Removal] --> [Binarization] --> [Output Result]

#### 2.2 MORPHOLOGICAL

##### OPERATIONS

Opening is commonly used in image processing applications such as object recognition and feature extraction, where it can help to eliminate unwanted background noise and improve the accuracy of the analysis. It can also be useful in preprocessing steps for optical character recognition (OCR), where it can help to improve the quality and legibility of the text.

In mathematical notation, opening can be expressed as:

$$A \ominus B \oplus B$$

where  $A$  is the original image,  $\ominus$  denotes erosion,  $\oplus$  denotes dilation, and  $B$  is a structuring element that defines the shape and size of the objects to be eroded and dilated.

Grayscale morphology is a variant of morphological image processing that works with grayscale images, rather than binary images. It involves the same basic operations as binary morphology, including erosion, dilation, opening, and closing, but the structuring elements used in these operations are grayscale, rather than binary.

In grayscale morphology, the value of each pixel in the structuring element determines its weight or contribution to the output pixel value. This allows for more precise control over the shape and size of the structuring element, and enables more accurate processing of images with complex or continuous intensity variations.

Grayscale morphology is commonly used in image processing applications such as edge detection, image segmentation, and feature extraction. It can also be useful in applications such as medical imaging and remote sensing, where it is important to analyze images with a high degree of accuracy and detail

### 3. FEATURE PROCESSING

The connected Component Analysis in cursive Tamil palm leaf scripts is a Herculean task, and it influences till the end of the character recognition process. Connected Component Analysis is applied to the preprocessed binary palm leaf text images to segment the text lines. The new way of approach, in-text line segmentation of Tamil palm leaf images is to determine whether the obstacle is present between the text lines. Whenever the strokes of the character exceed from the text zone and extend in the space between the lines, then it is considered to be an obstacle in this case.

#### 3.1 Connected Component Analysis

Connected component analysis is a technique used in image processing to identify and label the individual connected regions, or components, in a binary image. In a binary image, the foreground pixels (typically representing the object of interest) are set to one, and the background pixels are set to zero. In connected component analysis, the algorithm identifies all the groups of foreground pixels that are connected to each other, and assigns them a unique label or identifier. The resulting labeled image can then be used for further processing, such as character recognition or object detection. Connected component analysis can be performed using various algorithms, such as the two-pass algorithm or the depth-first search algorithm. It is commonly used in applications such as OCR (optical character recognition), where it can be used to segment individual characters in a text image

➤ First, the image is binarized by applying a thresholding operation to convert it into a binary image. Let  $I(x, y)$  be the input image and  $B(x, y)$  be the binarized image, then the thresholding operation can be represented as:

$$B(x, y) = \begin{cases} 1 & \text{if } I(x, y) > T \\ 0 & \text{if } I(x, y) \leq T \end{cases}$$

➤ Next, the connected components in the binary image are identified. This is done by assigning a unique label to each group of connected pixels in the binary image. The labels are typically integers starting from 1 and incremented for each new connected component. The process can be represented as:

$$L(x, y) = \begin{cases} 0 & \text{if } B(x, y) = 0 \\ L(p) & \text{if } B(x, y) = 1 \text{ and } p \text{ is a neighbor of } (x, y) \\ \text{new label} & \text{if } B(x, y) = 1 \text{ and } p \text{ is not a neighbor of } (x, y) \end{cases}$$

where  $L(x, y)$  is the label assigned to the pixel  $(x, y)$ ,  $p$  is a neighbor of  $(x, y)$ , and new label is a unique label not previously assigned.

➤ Finally, the connected components are segmented by extracting the pixels corresponding to each label. This can be represented as:

$$S_k = \{ (x, y) \mid L(x, y) = k \}$$

where  $S_k$  is the set of pixels belonging to the  $k$ -th connected component.

### 4. CONVOLUTIONAL NEURAL NETWORKS

A prevalent Deep Learning structure used for image recognition and classification tasks is the Convolutional Neural Network (CNN). It comprises several layers, including Convolutional, Pooling, and fully connected layers. The Convolutional layer uses filters to extract features from the input image, while the Pooling layer reduces computation by down sampling the image. Finally, the

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fully connected layer makes the ultimate prediction. The network discovers the best filters via backpropagation and gradient descent.

#### 4.1 CNN ARCHITECTURE

The Convolutional Layer's (CL) convolutional output is calculated using the convolution operation, which involves sliding a filter over the input image and computing the dot product between the filter and the corresponding pixels in the input. The formula for calculating the convolutional output of a single filter applied to an input image can be represented as follows:

Convolutional output = (Filter \* Input Image) + Bias

where '\*' denotes the convolution operation, 'Filter' represents the learnable parameters of the CL, 'Input Image' is the input image, and 'Bias' is a scalar value added to each element of the output to introduce a bias. The output produced by a single filter is a 2D feature map, and the convolutional output of the entire CL is a stack of 2D feature maps produced by all the filters applied to the input image.

A convolutional layer in a CNN applies a set of learnable filters (also called kernels or feature maps) to the input image to extract local features or patterns. The filters slide over the input image in a sliding window fashion, performing a dot product between their weights and the values of the corresponding pixels in the input image. The resulting output, known as a feature map, highlights the presence of local features such as edges, corners, and blobs in the input image. The mathematical operation performed by a convolutional layer can be expressed as follows:

$$y(i,j,k) = \sum \sum \sum x(m,n,l) * w(i-m+1,j-n+1,l,k)$$

where  $y(i,j,k)$  is the output feature map at location  $(i,j)$  and for the  $k$ -th filter,  $x(m,n,l)$  is the input pixel at location  $(m,n)$  and for the  $l$ -th channel, and  $w(i-m+1,j-n+1,l,k)$  is the weight of the filter at location  $(i-m+1,j-n+1)$  and for the  $l$ -th channel and  $k$ -th filter.

Pooling can be done using different techniques, such as max pooling or average pooling, where the maximum or average value within a sliding window is retained, respectively. Pooling helps to reduce the number of parameters in the network, making it more efficient and robust to variations in the input image. The mathematical operation performed by a pooling layer can be expressed as follows:

$$y(i,j,k) = f(\{x(i',j',k) \mid i' \in [iS, iS+H], j' \in [jS, jS+W]\})$$

where  $y(i,j,k)$  is the output value at location  $(i,j)$  and for the  $k$ -th channel,  $x(i',j',k)$  is the input value at location  $(i',j')$  and for the  $k$ -th channel,  $S$  is the stride, and  $H$  and  $W$  are the height and width of the pooling window, respectively. The function  $f(\cdot)$  can be either max or average pooling.

The output of a convolutional layer in a convolutional neural network (CNN) can be expressed mathematically as:

$$h(i,j,k) = f(\sum \sum \sum x(m,n,l) * w(i-m+1,j-n+1,l,k) + b(k))$$

where  $h(i,j,k)$  is the output feature map at position  $(i,j)$  and for the  $k$ -th filter,  $x(m,n,l)$  is the input value at position  $(m,n)$  and for the  $l$ -th channel,  $w(i-m+1,j-n+1,l,k)$  is the weight of the filter at position  $(i-m+1,j-n+1)$  and for the  $l$ -th channel and  $k$ -th filter,  $b(k)$  is the bias term for the  $k$ -th filter, and  $f(\cdot)$  is the activation function.

## 5. Results and discussions

As already said, the goal of this work is to develop a CNN model that is more effective than the existing models for the obtained cursive dataset. To construct the proposed neural PyTorch7 was employed as the Python-based framework for the network architecture. In order to do a comparison study, evaluations of several contemporary models, including LeNet5, ResNet (18/34/50), AlexNet, DenseNet121, InceptionNet v3, and others, were also carried out on these datasets. A system with Intel Core i3 Processors, 16 GB of RAM, and an NVIDIA graphics card with 4 GB of internal memory and 768 CUDA cores is used for all of these tests.

## References

- [1] D. Ganapathy, “Preserving India’s palm Leaf Manuscripts for the Future,” WAGLOBAL, Kerala, India, 2016.
- [2] N. S. Panyam, V. L. T.R., R. Krishnan, and K. R. N.V., “Modeling of palm leaf character recognition system using transform based techniques,” *Pattern Recognition Letters*, vol. 84, pp. 29–34, 2016.
- [3] K. P. Geena and G. Raju, “View-based feature extraction and classification approach to Malayalam palm leaf document image,” *International Journal of Innovative Research in Computer and Communication Engineering*, vol. 2, no. 5, pp. 264–267, 2014.
- [4] R. Chamchong and C. C. Fung, “A framework for the selection of binarization techniques on palm leaf manuscripts using support vector machine,” *Advances in Decision Sciences*, vol. 2015, Article ID 925935, 7 pages, 2015.
- [5] N. P. Challa and R. V. K. Mehta, “Applications of image processing techniques on palm leaf manuscripts-A survey,” in *Proceedings of the Conference on Cognitive Science and Artificial Intelligence*, CA, USA, February 2017.
- [6] S. Athisayamani, A. R. Singh, and A. S. Kumar, “Recurrent neural network-based character recognition system for Tamil palm leaf manuscript using stroke zoning,” in *Inventive Communication and Computational Technologies*, pp. 165–176, Springer, Singapore, 2021.
- [7] R. S. Ratheash and M. M. Sathik, “A detailed survey of text line segmentation methods in handwritten historical documents and palm leaf manuscripts,” *International Journal Of Computer Sciences And Engineering*, vol. 7, p. 99, 2019.
- [8] J. Ali and J. T. Joseph, “A convolution neural network-based approach for recognizing Malayalam handwritten characters,” *Malayalam Handwritten character recognition using cnn*, vol. 9, no. 12, 2018.
- [9] P. K. S. Balakrishnan and L. Pavithira, “Multi-font optical character recognition using Deep Learning,” *International Journal of Recent Technology and Engineering*, vol. 8, 2019.
- [10] M. A. Hossain and S. Afrin, “Optical character recognition based on template matching,” *Global Journal of Computer Science and Technology: C Software & Data Engineering*, vol. 19, 2019.
- [11] K. Baskar, “Manuscript Libraries in Tamil Nadu: a study of their organisation and preservation in the digital environment,” *Doctoral Dissertation in Information Science*, Madras University, Tamilnadu, 2018.
- [12] S. Devika and K. Vijayakumar, “Digitization of palm leaf manuscripts in Tamil Nadu (India): a study,” *Journal of Library Science and Research (JLSR)*, vol. 2, no. 1, pp. 1–10, 2016.
- [13] R. Narenthiran and P. Ravichandran, “Cataloguing and digitization of multilingual manuscript libraries in Tamil Nadu: an evaluative study,” *Journal of Advances in Library and Information Sciences*, vol. 5, no. 3, pp. 248–253, 2016.
- [14] T. K. M. Sageer and A. T. Francis, “Analysis of the palm leaves manuscripts collection for digital archiving: a case study of Sree Sankaracharya University of Sanskrit, Kalady,” *Journal Impact Factor*, vol. 5, no. 1389, pp. 90–99, 2016.
- [15] R. S. Sabeenian, M. E. Paramasivam, P. M. Dinesh, R. Adarsh, and G. R. Kumar, “Classification of handwritten Tamil characters in palm leaf manuscripts using SVM based smart zoning strategies,” in *Proceedings of the 2nd International Conference on Biomedical Signal and Image Processing*, pp. 18–21, Kitakyushu, Japan, August 2017.
- [16] B. Kiruba, A. Nivethitha, and M. Vimaladevi, “Segmentation of handwritten Tamil character from palm script using histogram program approach,” *International Journal of Informative and Futuristic Research*, vol. 4, no. 5, pp. 6418–6424, 2017.
- [17] S. Ghosh, A. Mahajan, and S. Banerjee, “Palm leaf manuscript conservation, the process of seasoning with special reference to Saraswati Mahal library, Tamilnadu in India: some techniques,” *International Journal of Information Movement*, vol. 2, pp. 122–128, 2017.
- [18] N. P. Challa and R. V. K. Mehta, “Applications of image processing techniques on palm-leaf manuscripts—a survey,” *Helix: e Scientific Explorer*, vol. 7, no. 5, pp. 2013–2017, 2017.
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- [19] R. Vinoth, R. Rajesh, and P. Yoganandhan, "Intelligence system for Tamil Vattezhuttuoptical character recognition," *International Journal of Computer Science Engineering and Technology*, vol. 8, no. 4, pp. 22–26, 2017.
- [20] M. Sornam and M. D. Poornima, "Tamil palm-leaf manuscript character segmentation using GLCM feature extraction," *International Journal of Computer Science and Engineering*, vol. 6, no. 4, pp. 167–172, 2018.
- [21] R. Devi Priya, R. Sivaraj, Ajith Abraham, T. Pravin, P. Sivasankar and N. Anitha. "MultiObjective Particle Swarm Optimization Based Preprocessing of Multi-Class Extremely Imbalanced Datasets". *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* Vol. 30, No. 05, pp. 735-755 (2022). Doi: 10.1142/S0218488522500209