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RESEARCH ARTICLE

Self-Adaptive Hybridized Lion Optimization Algorithm With Transfer Learning for Ancient Tamil Character Recognition in Stone Inscriptions

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ABSTRACT Tamil character recognition serves as a vital research problem in pattern recognition since there are many serious technical difficulties due to similarity and complexity of characters when compared with other languages. Stone inscriptions reveal details of luxury, lifestyle, economic status, cultural practices, administrative tasks followed by various rulers and dynasties of Tamil Nadu. Since ancient stone inscriptions are in existence for a longer period, there are possibilities of natural erosion and no early protection measures are available. The ancient stone inscriptions are always not complete which creates many difficulties in reading and understanding them and their aesthetic appreciation. There is a difficulty in recognizing Tamil characters mainly because of the characters with a number of holes, loops and curves. The number of letters in Tamil language is higher when compared to other languages. Even though there are various approaches provided by the researchers, challenges and issues still prevail in recognition of tamil text in stone inscriptions. In the existing systems, detection algorithms fail to produce desired accuracy and hence stone inscription recognition using transfer learning, a promising method is proposed here. Lion Optimization Algorithm (LOA) is applied to optimize brightness and contrast and then stone inscription images are pre-processed for noise removal and then each character is separated by identifying contours. Characters are recognized using Transfer Learning (TL), a Deep Convolution Neural Network-based multi classification approach. The proposed hybrid model Self-Adaptive Lion Optimization Algorithm with Transfer Learning (SLOA-TL) when implemented in images of stone inscriptions achieves better accuracy and speed than other existing methods. It serves as an efficient design for recognition of tamil characters in stone inscriptions and preserving tamil traditional knowledge.

INDEX TERMS Lion optimization algorithm, preprocessing, stone inscription, transfer learning, Tamil character recognition.

I. INTRODUCTION

India is the country rich in cultural heritage and monument sites. Tamilnadu has highest number of temple monuments in India. Most of the ancient temples in Tamilnadu are covered with stone inscriptions that were epigraphed during various pallava, pandian and chola periods. Ancient emperors wanted their fame to live eternal so that they have inscribed their achievements and gratification which is called as meikeerthi (True Fame). Poets wrote poems praising the kings and

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epigraphers engraved them on stones. These stone inscriptions stand as great sources to know about ancient history and valour of ancient people. The kings have inscribed government orders, practices, donations and events mainly on stones. They are very important to preserve and may help in making many strategic decisions for today.

Since ancient stone inscriptions are historical and exist for a longer period of time, natural erosion often dilapidates these stone inscriptions. In few temples, stones are cleaned using sand blasting that causes loss of details in stone inscriptions. Stone inscriptions created on different timelines have different character representations since characters evolve as years pass. Tamil Language has huge number of letters when compared to other languages. Syllable, the smallest unit in Tamil contains 12 vowels, 18 consonants and a special character called as Ayudha Ezhuthu(ஃ) Moreover, different combinations of vowels and consonants together create 216 compound characters and in total, tamil language possess 247 characters. The complexity of detecting curves, complicated letter structures, character combinations, more strokes and holes and other factors make it difficult to recognise Tamil characters. Because of these issues, heavy pre-processing is required.

Stone inscription images are captured from temples using camera and various pre-processing techniques like brightness, contrast optimization, binarization, denoising are applied and then characters are segmented. To easily understand the content of the stone images, correct brightness is important and contrast is helpful in bringing out the textures in the images which is important while segmenting the characters. Recently, varied versions of machine learning and deep learning algorithms are used for solving different kinds of problems in many applications [1]. The scenario has evolved where without machine learning / deep learning algorithms, no automation mechanism exists in today's modern world. These algorithms play a vital role in text and speech analysis especially character recognition.

Reference [2] studies various challenges that exist in Handwritten Character Recognition and found that ancient handwritten characters have more noise due to different colors and irregular patterns. It emphasizes that still efficient research works are needed in processing such handwritten characters in stones or any other platforms. Recently, [3] have also conducted a detailed survey of recognizing tamil characters from stone inscriptions. They also reported that there are still many issues in segregating foreground pixels from background images, varied intensities of light, similar background/ foreground colors, distorted inscriptions / stones, irregular shape and size of inscriptions. Image quality needs to be enhanced for better recognition accuracy and optimization of various parameters are required in tamil character recognition especially from stone inscriptions.

Optimization algorithms can be effectively used for attaining better solutions to many real-world problems [4], [5]. Reference [6] have found that lion optimization algorithm performs better in finding optimal solutions for any given complex problem. Moreover, [7] have used LOA for preprocessing handwritten images with tamil characters and used CNN for classification. Realizing the fact that LOA can be better used for classification, the proposed model proposes self-adaptive LOA model for preprocessing images of stone inscriptions. Transfer Learning algorithm is applied to recognize the segmented characters. Transfer learning (TL) is very efficient than other algorithms because it saves the intelligence gathered from one problem and applies it to another similar problem thereby saving time, cost and decreases computational complexity. Reference [8] have used Transfer Learning with inception-v3 model for recognizing tamil characters. Since pretrained models are used, they efficiently classify characters. Even though few methods are proposed by researchers, they are not that much efficient in analyzing tamil stone inscriptions especially when the inscriptions are 30-40 feet long. The epigraphy branch of the Archaeological Survey of India (ASI) has taken steps to analyze the inscriptions by preserving them as estampages in paper form. ASI also reports that still there are many unresolved challenges in preserving and analyzing the inscriptions and also converting them into the form of estampages.

With all these motivational factors, the proposed model combines SLOA and TL to perform efficient tamil character recognition with the following significant contributions:

i. Preprocessing of images is done using Self adaptive Lion Optimization Algorithm for automatic brightness and contrast optimization
ii. Binarization of image is done using Otsu method with adaptive thresholding strategy to find optimal threshold value and non-localized approaches for final denoising
iii. For minimizing salt and pepper/impulse noise, a median filter is proposed for reducing noise while retaining the edges and smoothing of image edges is achieved using Gaussian blur
iv. Transfer Learning with pretrained models is used to classify complex structure of ancient tamil characters with reduced execution time and better accuracy

SLOA retains a proper balance between exploration and exploitation by controlling the migrations in each pride. It is also more suitable for optimization of multimodal problems. The concept of nomad lions and adaptive roaming behavior make the algorithm to improve their exploration capability and ensure that the algorithm does not get stuck in local optimum value. When transfer learning with pretrained models is implemented together, training time will be greatly reduced. With this motivation, integration of both these methods are proposed for improving performance of stone inscription classification process.

The proposed method also has certain scope and limitations since all the methods cannot be equally implemented for all scenarios. The scope of the proposed SLOA-TL algorithm is limited for only tamil character recognition. Eventhough, the language chosen is tamil in this paper, it can also be made suitable for other languages provided training images of the corresponding language are given and trained. In this paper, tamil characters in stone inscriptions are chosen for implementation. However, it can also be used for recognizing tamil characters in paper (estampages), palmscripts or any other image forms.

II. LITERATURE REVIEW

Numerous researchers have performed character recognition from historical items and introduced various measures for identifying and classifying texts from them. Here, few literature papers are reviewed and their findings are given below.

Extraction of text-inscriptions from prehistoric articles has been under study for a long time. Earlier studies include two stage techniques namely supervised and unsupervised classification for recognition of handwritten tamil characters proposed in [9]. Machine learning methods are very commonly used in recognition of other language characters in the form of inscriptions and other formats which are given below.

Reference [10] demonstrated the use of SVM classifier to identify various ancient Kannada scripts. It is tested on a large number of Kannada epigraphical document images belonging to nine different periods. Reference [11] investigated the Han Dynasty with the help of stone carving images as well as existing image feature extraction methods. Reference [12] created an OCR system that can recognise handwritten English characters. Some preprocessing techniques were applied and a classifier called Multilayer Feedforward Backpropagation Neural Network classifies English characters. Reference [13]proposed a Transductive Support Vector Machine (TSVM) based periodic prediction system for epigraphical characters. In character classification, the TSVM model has better accuracy than SVM model.

Reference [14] suggested a Telugu character recognition system on palm leaf manuscripts. Using a specifically built scanner, 3D features of those characters are retrieved in this manner. The 3D features are recognized using 2D Fast Fourier Transform (2D-FFT) and 2D Discrete Cosine Transform (2D-DCT). Reference [15] have devised a method for determining the period on which the given ancient Kannada scripts actually belongs to. Image acquisition, noise removal, character segmentation, classification and recognition were all part of this approach. It had correctly identified four different periods of characters with good accuracy. Reference [16] devised a method for recognizing Malayalam characters. The feature extraction process was broken down into three steps. The first stage was used to classify the characters based on characteristics such as the count of corners, endings, bifurcation, loops etc. In the second stage, the character's specific classes are determined and in the third stage, the characters' likelihood of recurrence are determined.

Reference [17] proposed a novel feature extraction method for Handwritten Devanagari Vowels recognition. Histogram oriented gradient features are extracted. For categorization, the retrieved characteristics are chosen. Artificial Neural Network is used as a classification tool. The accuracy of handwritten Devanagari Vowel recognition with SVM classifier is better than other methods.

Reference [18] worked on developing an application that could recognize ancient Sinhala inscriptions using Optical Character Recognition (OCR). Experiments were conducted to assess the recognition rate of the OCR technologies. Convolutional Neural Network (CNN) has shown optimal OCR solution after reviewing when compared with other methods. For nine Sinhala characters, the model was examined. For pre-processed images, the CNN model was 95.2 % accurate, while the ANN model was 85 % accurate.

Reference [19] used a deep Convolutional Neural Network to construct an efficient Adversarial Feature Learning strategy to understand prior knowledge that is being depicted in printed data and writer-independent semantic features to enhance the performance of handwritten Chinese character recognition. Reference [20]evaluated different thresholding techniques for processing Palm-leaf Manuscript images. Filtering and picture enhancement were done as part of the preprocessing stage. Decision-based median filter first filters the noise contrast and then local adaptive histogram equalization improves quality of the image. Otsu global thresholding and other local thresholding techniques such as Niblack, Sauvola and Bernsen algorithms had been used for segmentation.

Reference [21] developed a novel ancient stone inscribed character recognition system that is independent of any language script and used histogram of Oriented Gradients. This feature counts the number of times a gradient orientation appears in certain areas of an image. Here, digital photos of 11th century stone inscriptions are used to create a database. After the characteristics are computed, the system is taught to classify them into present characters using Support Vector Machine.

Reference [22] described a method for recognizing old handwritten Tamil characters inscripted on Palm Leaves. Convex hull bounding was used to segment the characters which were then converted into two different formats: BCV (Binary Coded Value) and GLCM (Gray-Level Co-occurrence Matrix). The Modified Adaptive Back Propagation Network (MABPN) algorithm is hybridized with Shannon activation function for training the features retrieved from segmented characters. It also shows better results on stone inscriptions. In detecting and classifying tamil characters in stone inscriptions, MABPN-BCV (model 1) has better accuracy than that of MABPN-GLCM. Reference [23]proposed palm leaf manuscript character recognition. All 12 vowels in tamil are recognized with the help of B-spline curves. The vowels are detected by recognizing based on combination of curves. For the letter "அ", this proposed approach has a maximum accuracy of 92% and a minimum accuracy of 67 % for the letter "ஐ".

Reference [24] proposed ancient text identification model that encompasses binarization using selection encoder and decoder techniques. At character level, the binarized images are further divided using the Seam Carbel approach. Characters are recognised with a three-layer Convolutional Neural Network. Reference [25] have done binarization on terrestrial and underwater stone inscriptions. The Modified Bi-level

TABLE 1. Literature of methods for recognizing tamil characters.

Literature	Method used	Description
[31]	Kohonen SOM (Self-Organizing Map)	Detects online Tamil characters and SOM does not apply to the cursive characters
[32]	Vector Space model & ANN models	Tamil document categorization demands high-dimensional space for representing documents
[33]	Canny Edge Detection Algorithm	Picture differentiation is performed and then ANN is integrated to perform final classification
[34]	Principal Component Analysis (PCA) and CNN	Feature extraction is done for enhanced recognition of Tamil characters
[35]	Convolutional Neural Network architecture (ConvNet)	Offline isolated recognition system for Tamil characters
[36]	Otsu thresholding method, ANN	OCR based model for both ancient and modern tamil character recognition
[37]	Convolutional Neural Network based model	Trained in offline mode with Tamil characters
[38]	VGG16 and CNN	16 layers of Feed forward deep learning and Transfer learning are used to perform classification
[39]	Soft computing techniques and boggle algorithm	Segmented image is decomposed using hybrid feature extraction technique along with Chi-square test and final characters are converted into word form
[40]	ANN & Opposition Based Grey Wolf Optimization Algorithm (OGWO)	ANN recognizes ancient south Indian characters and their weights are updated using OGWO
[41]	Image-based Character Pattern Identification and Modified Speeded Up Robust Feature with Bag of Grapheme (MSURF-BoG) algorithm	Identify significant spots of the input characters of varied perspectives

Thresholding (MBET) strategy was developed and compared to a number of existing thresholding techniques, including the Niblack, Bernsen, Sauvola, Otsu and Fuzzy C means methods.

Reference [26] have proposed Long short-term memory (LSTM) based training for recognizing Tamil, Sinhala and English characters in documents. Reference [27] have implemented Optimized Deep Neural Networks together with Zernike Moments and Simplex Method where preprocessing operations like Binarization, De-noising, character segmentation, size normalization and feature extraction are done. Back Propagation deep Neural Network performs classification of tamil characters in which the neural network is optimized by using simplex method. Feature extraction was done using Zernike moment and classification was performed using multilayer feed forward neural network and back propagation algorithm.

Reference [28] have proposed system for object detection in balinese script. Manuscript images are pre-processed using Sobel and Canny edge detection algorithm. Findcontour() method processes balinese manuscript after image processing for object detection. Finally, discovered objects are categorized into three categories namely Balinese script, noise and hole. Reference [29] have tried using Modified ResNet-18 algorithm for recognizing Bangla handwritten characters. ResNet model is chosen as the underlying architecture since it produces better results than other compared architecture models in different applications and the same is proved in this implementation too.

Reference [30] have developed a network using the principles of deep learning for inferring the shape of kanji characters in order to predict pixel-wise text sections inscripted on stone monument images. This method was trained on a deep neural network using pseudo-inscription images, which was created by synthesizing a shaded image which depicts the engraved text and stone textures.

From the literature review, it is observed that there exists large scope to implement more efficient and effective strategies for recognizing tamil characters in stone inscriptions. Models developed using deep learning strategies have been proven to be efficient for varied applications and hence the proposed methodology is making an attempt to implement improved version of much appreciated transfer learning method for character recognition.

III. PROPOSED METHODOLOGY

The paper proposes better pre-processing and character segmentation strategies for recognizing text in stone inscriptions. Rather than implementing the standard OCR, performance can be enhanced by following the proposed preprocessing techniques. Sample stone inscription image is shown in figure 1 and overall flowchart of the proposed SLOA-TL is depicted in figure 2.

A. PRE-PROCESSING

Preprocessing of images of stone inscriptions include various steps which are explained below.

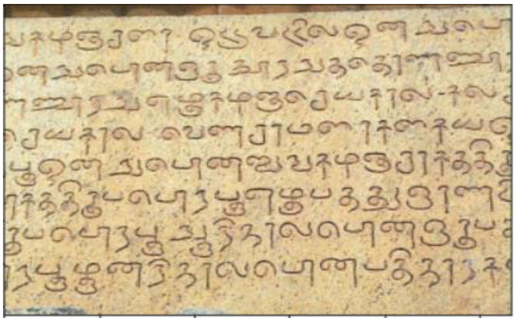

FIGURE 1. Stone Inscription image.

1) BRIGHTNESS AND CONTRAST OPTIMIZATION

Brightness is a measure of luminance or intensity. The amount of color or grayscale differentiation that exists between various image components in both analogue and digital images is referred to as contrast. To retrieve the details and to reduce noise in stone images, optimizing brightness and contrast is essential. Optimization of brightness and contrast is done automatically using optional histogram clipping. The image obtained after optimization of brightness and contrast is shown in figure 3. The level of image contrast and brightness is proposed to get adjusted using values of alpha (α) and beta (β) which are called gain and bias parameters respectively. The process is evaluated using the following equation (1).

$$g(i,j) = \alpha \cdot f(i,j) + \beta \tag{1}$$

To calculate the values of alpha and beta, rather than choosing values randomly, LOA optimization is implemented. Random values do not always result in better solution since they may fail to exhibit the original properties of solutions. Critical parameter values in an algorithm always need to be optimized in order to yield better solutions. Hence, LOA is used to automatically choose the values of α and β which in turn directly influence the brightness and contrast levels.

a: LION OPTIMIZATION ALGORITHM (LOA)

LOA serves as a meta-heuristic method where a set of randomly generated solutions known as lions establish an initial population. N such solutions constitute the population where each solution contains features α and β which need to be optimized. The solution is represented as below:

$$\text{Solution (Lion)} = [\alpha, \beta]$$

Few lions in the original population (N) form the nomads and the remaining population is chosen as Prides (P) at random. Among nomad lions, S% of the individuals is female and the remainder is male. The solutions are chosen in such a way that they contain different combinations of brightness and contrast.

Few female lions from each pride search for prey in groups for serving their prides. The hunters usually possess their own specific heuristic for encircling and catching the prey. Usually, the lioness follows the same pattern for hunting their prey. During hunting, each lioness adjusts its position using its own current position and also positions of their group members. In general, hunters attack their prey from opposite sides for accurate targeting and hence Opposition based learning is used here which is found to be better for solving optimization problems. Lions are divided into 3 groups/wings namely center, left and right as given in figure 4.

Classification accuracy of Random forest (RF) algorithm represents the fitness value of each lion (solution). The best-obtained solution in previous iterations is referred to as the best-visited location for each lion and it is updated as the optimization process progresses. Territorial Takeover is the process of retaining just the best male and female solutions that are capable of outperforming new solutions to a given amount, while eradicating existing solutions from the pride.

Hunter will be improving his fitness continuously and at the same time, PREY usually attempts to escape from the hunter and obtain its new position as estimated in eqn. (2).

$$\text{PREY}' = \text{PREY} + \text{rand}(0, 1)\text{x PI x}(\text{PREY} - \text{Hunter}) \tag{2}$$

where PREY represents the PREY's current position, Hunter refers to the new position used by the hunter to attack the prey and PI indicates the % of hunter's fitness improvement.

The encircling of prey by hunter groups for left and right wings are given by eqn. (3) as

$$Hunter' = \begin{cases} rand\left((2\times PREY - Hunter), PREY\right), \\ \quad (2\times PREY - Hunter) < PREY \\ rand\left(PREY, (2\times PREY - Hunter)\right), \\ \quad (2\times PREY - Hunter) > PREY \end{cases} \tag{3}$$

where Hunter refers to the HUNTER's current position and Hunter' indicates the HUNTER's new position. The updated positions of center hunters are represented by using following eqn. (4).

$$\text{Hunter}' = \begin{cases} rand\left(Hunter, PREY\right), Hunter < PREY \\ rand\left(PREY, Hunter\right), Hunter > PREY \end{cases} \tag{4}$$

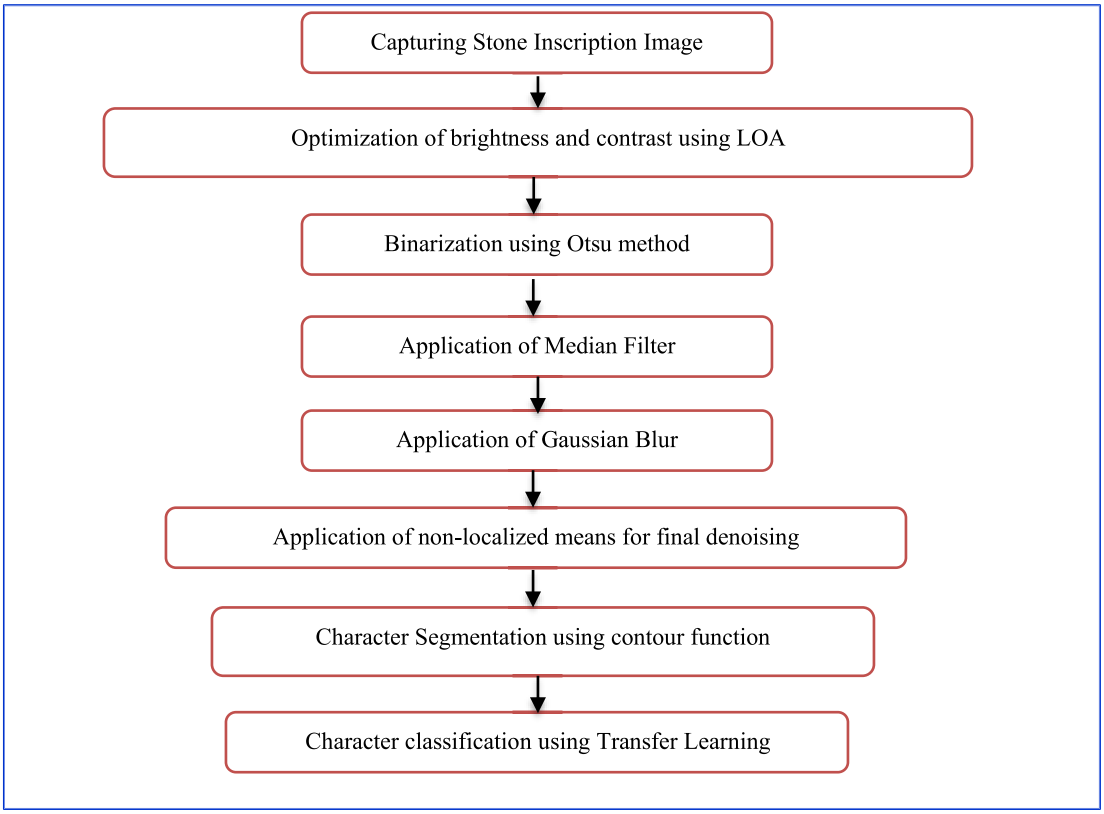

FIGURE 2. Proposed system flow.

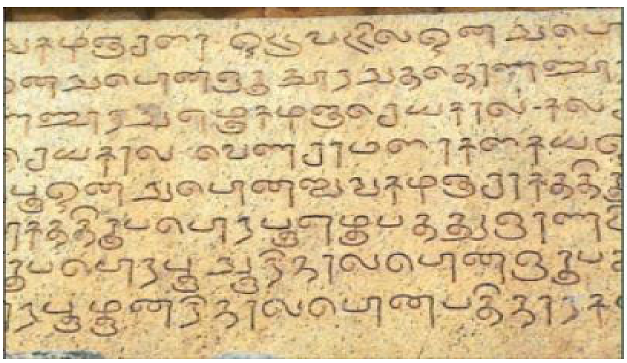

FIGURE 3. Brightness contrast optimization.

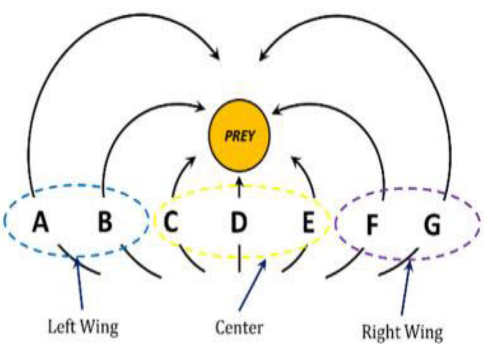

FIGURE 4. Groups of Lion wings (Center, left and right).

The territories of each pride contain the personal best solution of all of its members which help to retain the best solutions

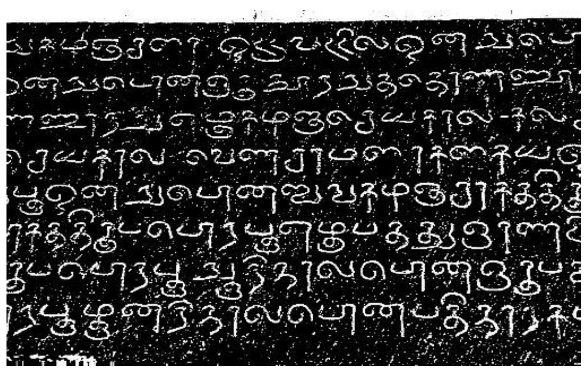

FIGURE 5. Binarized image.

for the algorithm. Over the iterations, they can be used to improve the solutions of Lion Optimization algorithm. The new positions for female lions are represented by eqn. (5).

$$\begin{aligned} Female\ Lion' = {} & Female\ Lion + 2 \times D \times rand(0,1)\{R1\} \\ & + U(-1,1) \times tan() \times D \times \{R2\} \end{aligned} \tag{5}$$

$$\begin{aligned} \{R1\}.\{R2\} &= 0 \\ ||\{R2\}|| &= 1 \end{aligned}$$

Female Lion represents the lion's current position, D indicates the lion's position identified using tournament selection in the pride's territory. The value of {R1} indicates

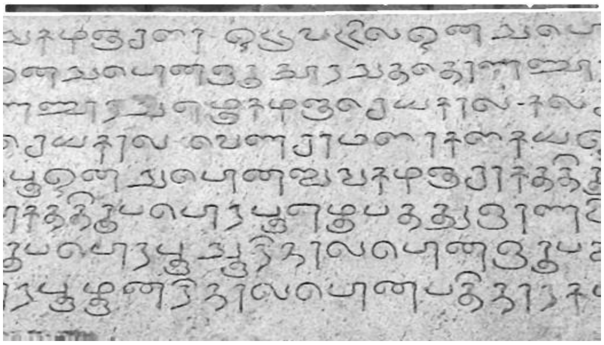

FIGURE 6. Median filtered image.

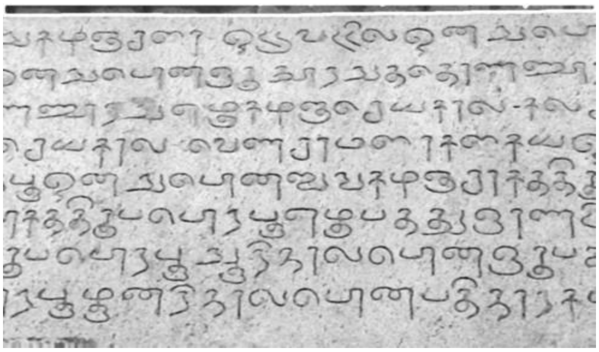

FIGURE 7. Gaussian blur added image.

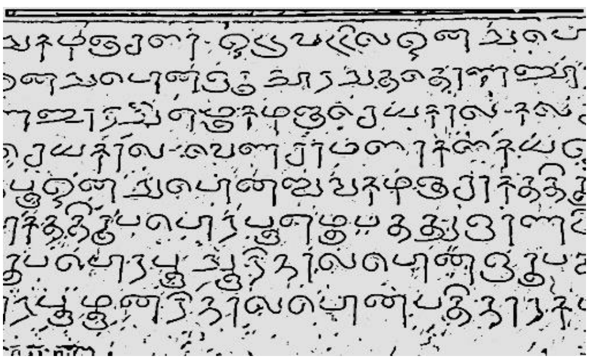

FIGURE 8. Final preprocessed image.

the starting location which is previous position of the lion and it heads towards {R2}. Both these vectors {R1} and {R2} are perpendicular to each other. The resident male lion also roams to some randomly selected locations and if the identified new positions are better than the previous ones, it immediately updates its local best solution.

After this, mating is done to create new offsprings. Predefined c % of female lions in every pride gets crossed over with one or more random resident males. But, nomad lions mate with only one random male. After a pair for mating is selected, the two offsprings are generated

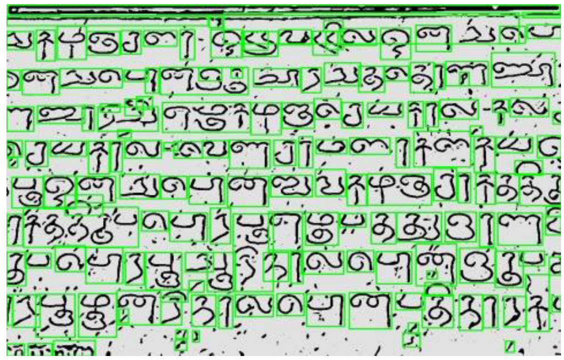

FIGURE 9. Character segmentation.

using the eqns. (6) and (7).

$$Offspring_j 1 = \beta \times Female\ Lion_j + \sum \frac{1-\beta}{\sum_{i=1}^{NR} S_i} \times Male\ Lion_j^i \times S_i \tag{6}$$

$$Offspring_j 2 = (1-\beta) \times Female\ Lion_j + \sum \frac{\beta}{\sum_{i=1}^{NR} S_i} \times Male\ Lion_j^i \times S_i \tag{7}$$

where dimension is indicated by j, $\mathbf{S_i}$ will take the value of 1 if male i is used for crossover and 0 otherwise, NR indicates the count of resident males existing in the pride and $\boldsymbol{\beta}$ represents a random value which follows normal distribution with mean value of 0.5 and the standard deviation is chosen as 0.1. Two random offsprings generated are chosen as male and female. M % of genes are mutated where some random number replaces them. By completing all these operations, LOA generates population of new cubs with new inherited characters from their parents. Defense operation is carried out effectively where the mature males fight with other males aggressively. The beaten lions with low fitness will be removed out of the pride and become nomads whereas high fit lions are retained in the population by becoming resident males.

During migration operation, few randomly selected female lions become nomads and they migrate out of the pride. The old and new nomads are sorted using the values of their fitness and the optimal ones are again pushed into the population to fill the place of the removed lions. This process ensures that required amount of diversity is always maintained in the population.

The algorithm is terminated when specified number of iterations, CPU time or required fitness value is achieved as defined by the user. Finally, the solution with best fitness is chosen and the corresponding values of α and β are chosen for further optimization of brightness and contrast.

2) BINARIZATION

In the process of binarization, the pixel values are separated into black and white hues (0 &1). It is vital to distinguish the items of interest from the background in picture enhancement or analysis problems. Bgr color image is transformed into grayscale image and the grayscale image is then transformed to a binary image. Otsu's algorithm performs binarization and the resultant binarized image is shown in figure 5.

a: OTSU'S ALGORITHM

Otsu's approach follows adaptive thresholding to binarize the images. The best threshold value for the input image is estimated by assessing the between-class variance (or within-class variance) of all possible threshold values (from 0 to 255). Initially, histogram for the input image is created and then for optimizing threshold, the minimum within-class variance Vw (or maximum between-class variance Vb) is found.

$$\sigma^2 = \frac{\sum_{i=0}^{N} (X_i - \mu)^2}{N} \tag{8}$$

where σ^2 is variance; X_i represents the pixel value, μ and N represents mean and number of pixels in the image.

3) MEDIAN FILTER

Median filtering, a nonlinear method for removing image noise is implemented since it is found to be better in noise reduction while retaining the edges. The 'salt and pepper' sounds are also efficiently handled by this mechanism. It replaces each value using median value of adjacent pixels by going through pixel by pixel. Output image post implementation of median filter is shown in figure 6.

4) GAUSSIAN BLUR

A Gaussian blur filter, a low-pass filter capable of reducing noise (high-frequency components), blur image regions and smoothening the edges. To achieve the desired effect, an odd sized symmetric that is passed through each pixel of the region of interest is used as the filter. The resultant Gaussian filtered image is shown in figure 7.

5) NON–LOCALIZED FILTER

The mean value of all pixels in the image is estimated based on their similarity to the target pixel during filtering and is called as non-localized mean filtering. When compared to local mean methods, the results can be significantly better because of less image information loss and post-filtering clarity. Final preprocessed image is shown in figure 8.

B. CHARACTER SEGMENTATION

Character segmentation is a technique for breaking down a series of characters in an image of into individual symbol images. Characters are segmented using findcontour function in opencv framework of python. A contour is the list of points that form boundary of the shape. Topological structural analysis is used to recover contours from the binary image. Retr_external is used as contour retrieval mode which retrieves outer contours only. Contour approximation method used is chain_approx_tc89_kcos which is used as the shapes are curved and are not simple polygons. Identified contours are bounded with rectangles and the bounded characters are saved as images which is shown in figure 9.

C. CHARACTER RECOGNITION

As the final step, Inception model in transfer learning algorithm is trained on vowels (uyir eluthukal-12+1[autha eluthu]), consonants (mei eluthukal-18), consonants combined with vowels (uyirmei eluthukal-216) and granthaletters(5). Some soul-body letters are combination of two individual characters. Since each character is segmented separately, the algorithm is trained on 156 classes of characters given in figure 10.

Each class contains images of modern handwritten tamil characters, modern and middle-aged stone inscription characters. AveragePooling2D is used in both training and classification steps to estimate the mean value for patches in the feature map each with pool size of 2 × 2. The activation function value is then flattened to form a vectorized feature map, with two fully connected layers: (i). one with 128 nodes and (ii). the other with 156 nodes for classification of characters. The probability for each class label is then calculated using the activation function value from the second fully connected layer which is provided to the softmax layer. After classification, predicted class labels are concatenated and given as the output.

FIGURE 10. Handwritten characters taken for classification.

1) TRANSFER LEARNING

Transfer learning is a Deep Learning (DL) algorithm that stores and applies the incurred knowledge to obtain solution for a different but related problem. For instance, skills learnt during learning process of detecting vehicles can be applied to trucks. Eventhough, they are practically dealing with different scenarios, learning from one problem can be transferred to solve another problem. Such can enhance the reinforcement learning agent's sample efficiency dramatically. The diagrammatic representation of the proposed system is shown in figure 11.

In transfer learning, using pre-trained images, large amount of time required for training process can be greatly reduced. Here, five different pre-trained models such as Inception V3, VGG 16, VGG 19, Xception and ResNet 50 are compared. Basic parameters like batch size, training testing ratio and number of epochs are set. Weights of all the other layers are fixed except for the last layer. The input images are provided to the model for training and tested is then performed on test images. The number of epochs indicates the number of times the algorithm is executed on the dataset and batch size indicates the number of training samples. Parameters like number of epochs and batch size need to be carefully fixed to achieve better results. The output of this classification process serves as the identified tamil character from the stone inscription.

IV. RESULTS AND DISCUSSION

The images of stone inscriptions are captured from temples using camera. Stone inscription images may be dull due to the lighting conditions and may contain lot of noise. The dataset is created from hp labs (hpl) handwritten tamil characters as given in table 2 and stone inscription characters are manually classified for training the transfer learning model. Stone inscription images were taken from Thirumuruganpoondi temple (9 km from Tiruppur, India.) built by the Kongu Cholars. 68 recorded inscriptions by the king Vikrama chola I can be seen on the sanctum walls and around precinct.

The proposed method SLOA-TL can recognize and classify characters based on the attributes extracted in feature extraction phase of transfer learning. The parameters used in the implementation and their values are given in table 3. Different training - testing ratios (80:20, 60:40, 70:30) were considered and better results were found in the ratio of 70:30. Similarly, with the training testing ratio of 70:30, the experiments are conducted with different number of epochs like 10, 15, 20, 25 and 30. From these initial runs, it was observed that the results are better when the algorithm is allowed to run for 25 epochs. Hence, the number of epochs for all further experiments are fixed as 25. All the experiments were conducted in machine possessing 3.7 GHz Intel Core i7 processor and 16 GB RAM. Implementation is done using the language Python 3.8 in Windows 10 operating systems.

A series of 11690 images were used for training and 3915 images for testing. These images were a mix of handwritten tamil characters and stone inscription characters. The total amount of character images in both datasets used training and testing sets are shown in table 4. Table 5 shows different architecture models used for experiments namely Inception V3, Xception, VGG19, VGG16 and ResNet50 and the number of layers in each model. The number of layers for each model is determined by experimenting with different possible values and the identified optimal number of layers for the given input is specified in table 5.

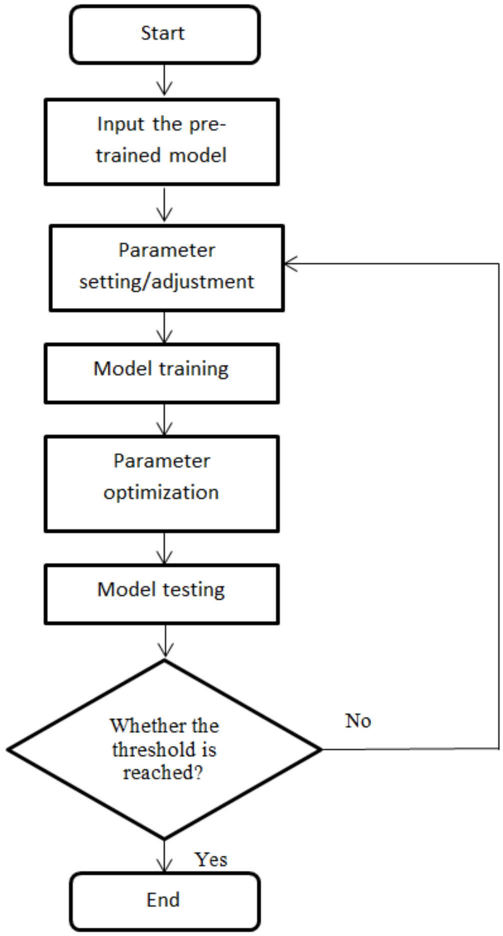

FIGURE 11. Flow diagram of transfer learning.

TABLE 2. hpl-tamil-iso-char dataset with class labels.

அ	ஆ	இ	ஈ	உ	ஊ	எ	ஏ	ஐ	ஒ	ஓ	ஔ			
0	1	2	3	4	5	6	7	8	9	10	11			
க	ங	ச	ஞ	ட	ண	த	ந	ப	ம	ய	ர	ல	வ	ழ
12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
ள	ற	ன	ஸ	ஷ	ஜ	ஹ	க்ஷ	கி	ஙி	சி	ஞி	டி	ணி	தி
27	28	29	30	31	32	33	34	35	36	37	38	39	40	41
நி	பி	மி	யி	ரி	லி	வி	ழி	ளி	றி	னி	ஸி	ஷி	ஜி	ஹி
42	43	44	45	46	47	48	49	50	51	52	53	54	55	56
க்ஷி	கீ	ஙீ	சீ	ஞீ	டீ	ணீ	தீ	நீ	பீ	மீ	யீ	ரீ	லீ	வீ
57	58	59	60	61	62	63	64	65	66	67	68	69	70	71
ழீ	ளீ	றீ	னீ	ஸீ	ஷீ	ஜீ	ஹீ	க்ஷீ	கு	ஙு	சு	ஞு	டு	ணு
72	73	74	75	76	77	78	79	80	81	82	83	84	85	86
து	நு	பு	மு	யு	ரு	லு	வு	ழு	ளு	று	னு	கூ	ஙூ	சூ
87	88	89	90	91	92	93	94	95	96	97	98	99	100	101
ஞூ	டூ	ணூ	தூ	நூ	பூ	மூ	யூ	ரூ	லூ	வூ	ழூ	ளூ	றூ	னூ
102	103	104	105	106	107	108	109	110	111	112	113	114	115	116
ா	ெ	ே	ை	ஸ்ரீ	ஸு	ஷு	ஜு	ஹு	க்ஷு	ஸூ	ஷூ	ஜூ	ஹூ	க்ஷூ
117	118	119	120	121	122	123	124	125	126	127	128	129	130	131
க்	ங்	ச்	ஞ்	ட்	ண்	த்	ந்	ப்	ம்	ய்	ர்	ல்	வ்	ழ்
132	133	134	135	136	137	138	139	140	141	142	143	144	145	146
ள்	ற்	ன்	ஸ்	ஷ்	ஜ்	ஹ்	க்ஷ்	ஃ						
147	148	149	150	151	152	153	154	155						

Each model is experimented with 30 runs and each run for 25 epochs to get better results and the comparison results of five models are shown in table 6.

It was observed from the literatures that Inception V3 model is found to be better than other models. The same scenario is observed in our experiments also. For the given stone inscription datasets, Inception v3 model outperforms all other models in terms of execution time and accuracy. The underlying architecture of Inception model is efficient and the layers are trained in such a way that high classification accuracy is achieved. Inception v3 model is experimented with varying number of epochs to identify the optimal count.

TABLE 3. Selected parameters and values.

Parameters	Values
Batch size	16
Training Testing Ratio	80:20,70:30, 60:40
Number of Epochs	10,15,20,25,30
LOA Population Size	40
Number of Prides	4
% of Nomad lions	0.4
Roaming %	0.2
Probability of Mutation	0.15
Probability of Crossover	0.75
Immigration rate	0.3

TABLE 4. Dataset split for training and testing.

Dataset	Total No. of images	Training set (70%)	Testing set (30%)
Stone inscription character images	10403	7793	2610
Handwritten character images	5202	3897	1305

TABLE 5. Models and their corresponding number of layers.

Model	No. of layers
Inception V3	48
Xception	71
VGG19	16 (convolutional)+3 (fully connected)
VGG16	16
ResNet 50	50

Execution time and accuracy of the experiments are shown in table 7. It is observed that 30 epochs had shown better accuracy among all choices but when the number of epochs increase, there is an increase in execution time and also improvement in accuracy. When accuracy is very much desired, the execution time has to be compromised. Hence, the proposed method SLOA-TL are run for 30 epochs in further experiments.

TABLE 6. Comparison of performance of five models for SLOA-TL.

Model	Time (s)	Accuracy (%)	Precision	Recall	F1 Score
Inception V3	201.0	97.533	0.94	0.91	0.92
Xception	443.6	90.828	0.90	0.87	0.88
VGG19	309.2	87.776	0.87	0.85	0.85
VGG16	342.6	83.442	0.81	0.76	0.78
ResNet 50	474.2	72.334	0.72	0.65	0.68

TABLE 7. Performance of inception models with varying epochs.

Epoch	Time (s)	Accuracy (%)
10	95.8	94.63
15	134.6	95.99
20	170.0	96.23
25	201.8	97.53
30	215.3	97.69

The performance comparison of various pre-existing models like Optimized DNN [27], Three-layer CNN (TCNN) [24], MABPN-BCV [21], SVM [17] and CNN [18] in terms of their accuracies is shown in table 8. The proposed SLOA-TL outperforms pre-existing systems with accuracy of 97.81%. Other measures like sensitivity, specificity, F1 score and Area Under Curve (AUC) are also compared and their results also show superior results. The characters detected are represented by rectangle (Bounding) boxes and saved as images and classified. The sample predictions are shown in table 9. Transcripted text from stone inscriptions is shown in figure 12. Further, the obtained test results are validated with ten-fold cross validation and the results are reported in table 10. Simple implementation of CNN shows least classification accuracy and TCNN results in comparatively better performance. The proposed SLOA-TL depicted its superiority by achieving 97.25%. The performance of SLOA-TL is superior to other methods since it employs Lion Optimization Algorithm for optimization of color and brightness and Adaptive Otsu's method for binarization. The images which are not even clear are also improved by LOA and they are then classified using pre-trained Transfer Learning. The improved image quality results in better accuracy and pre-trained transfer learning completes the process in less time.

The benefits of LOA contribute to the final performance in these following ways. Local best value stored for each lion provides much reliable and significant knowledge gained in the population. The concept of prides also assists in retaining the best solutions which are identified over all the previous generations. Resident males also roam across different locations to gather information from their neighbors with required knowledge which improves the process of exploitation to a great extent and serves as a good local search mechanism.

The concept of encircling in the hunting process also has benefits of maintaining the neighbors in circle shape so that the hunters can easily get close to the prey in all sides and the solutions can also be prevented from getting stuck in local optimum.

TABLE 8. Comparison of SLOA- TL with existing systems.

Algorithms	Accuracy (%)	Sensitivity	Specificity	F1 Score	AUC
DNN	92.80	0.91	0.93	0.94	0.89
CNN	74.24	0.71	0.69	0.62	0.72
MABPN-BCV	87.50	0.88	0.87	0.84	0.80
SVM	85.74	0.80	0.74	0.79	0.81
TCNN	93.20	0.89	0.91	0.90	0.90
SLOA-TL	97.81	0.95	0.92	0.95	0.94

TABLE 9. Sample prediction results of LOA-TL.

Segmented Character	Actual Class Label	Predicted Class Label
	29	29
	24	24
	20	20

FIGURE 12. Sample transcripted stone text.

TABLE 10. Comparison of Tenfold cross validation accuracy.

Algorithms	Cross validation Accuracy (%)
DNN	92.56
CNN	73.12
MABPN-BCV	83.47
SVM	86.89
TCNN	92.56
SLOA-TL	97.25

A. STATISTICAL TEST

In order to test the experimental results statistically, Friedman test, a non-parametric test is conducted. A selected pair of algorithms p_1 and p_2 are compared with respect to the Friedman Statistic using the following equation.

$$Z = \frac{R_{p1} - R_{p2}}{\sqrt{\frac{n(n+1)}{6m}}} \tag{9}$$

where m represents the number of datasets and n indicates the total number of algorithms which are compared. R_{p1} and R_{p2} refer to the average rank of the algorithms p_1 and p_2 respectively. In Table 11, average ranking of all six compared algorithms are given.

TABLE 11. Average rank of algorithms.

Algorithms	Average Rank
DNN	2.56
TCNN	3.12
MABPN-BCV	3.47
SVM	3.15
CNN	2.56
SLOA-TL	4.83

The proposed algorithm SLOA-TL shows higher average rank than other remaining five algorithms which are compared. The next table 12 shows the p values obtained from Nemenyi and Shaffer procedures. The z values and p_{Nem} and $p_{Shaffer}$ values also depict that TCNN is close in performance to SLOA-TL than other compared methods. From the table, it is noted that based on both these procedures null hypothesis stating that there exists no significant difference between the algorithms is rejected with the unadjusted p value of less than 0.5. The obtained chi square value in the given test is 9.488 for the given p value of 0.0317 with degrees of freedom and significance value (α) chosen as 4 and 0.05 respectively. TCNN shows close performance to the proposed algorithm in terms of p values which show that TCNN version of CNN can be used for classification, if CNN versions are required for classification of any dataset. The performance of algorithms is different and the results also emphasize that the proposed algorithm is superior than other compared algorithms. The proposed method shows its supremacy due to the fact that hybrid combination of Lion optimization algorithm and transfer learning together helps the algorithm in reaching optimal solutions.

TABLE 12. Freidman – Nemenyi and Shaffer procedure values.

Algorithms	z	p_{Nem}	$p_{Shaffer}$
DNN ~ SLOA-TL	2.56	2.51	2.34
CNN ~ SLOA-TL	3.12	2.03	2.09
MABPN-BCV ~ SLOA-TL	2.47	2.86	3.22
SVM ~ SLOA-TL	3.15	3.67	2.95
TCNN ~ SLOA-TL	2.56	1.68	2.07

V. CONCLUSION AND FUTURE WORKS

The paper has thus put forth a simple novel framework for reading complex tamil font characters on stone inscriptions. When the input images are pre-processed optimally and clear image is presented to the classification algorithm, better results can be achieved and this is evident from the proposed methodology. Much effort needs to be spent on preprocessing than classification and hence the proposed SLOA-TL carefully performs all the tasks with the help of efficient strategies and optimal solutions are identified and implemented so that the overall performance is superior. The transfer learning method takes into account all the existing grid cells in the frame to detect multiple objects existing in each frame such that it improves the accuracy of character classification in less time. This system classifies all the characters in middle and modern tamil languages. As a future work, the system can be enhanced to classify transcriptions in other forms and other languages. The accuracy of the system decreases at certain situations like when the stone inscriptions are barely visible or camera quality is too low or lighting conditions are poor. As a future work, classification of tamil stone inscriptions can be implemented by other optimization and meta heuristic methods.

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