International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-8 Issue-5, June 2019

PNN and Deep Learning Based Character Recognition System for Tulu Manuscripts

C K Savitha, P J Antony

ABSTRACT--- The main intention of the work is to implement a machine learning based offline Hand written character recognition (HCR) system for South Indian ancient language called Tulu. Degraded images are preprocessed with adaptive thresholding based binarization, median filter based noise removal and skeletanization processes. The classification of characters is done by the help of a Probabilistic neural network (PNN) and Deep convolution neural network (Deep ANN) models. Wavelet transform and Zone wise gradient direction values of skeletons of characters are extracted to form feature vectors, which are used for training the PNN model. Best recognition efficiency of 97.05% achieved for Tulu characters from degraded paper documents, 98.12% for Tulu numerals and 88.07% is achieved for Tulu palm leaf characters using Deep CNN model compared to PNN. The results verified that the proposed methodology outperforms from the present state of art models.

Index Terms— Handwritten Character Recognition; Palm Leaf; PNN; Deep ANN; Tulu; Wavelet.

I. INTRODUCTION

Historical documents were the first writing that contains significant data about an individual, spot or event, often archives suffer from degradation problems such as smear, rust, dust, etc. So, it is hard to identify the information present in degraded manuscripts. Character recognition field is a champion among the most significant territories in the field of pattern recognition. Many works are going on in this field. But the major challenge in that is recognition of handwritten characters from the degraded documents. By using the binarization and various pre-processing technique it can improve the quality of degraded manuscripts and can make these manuscripts clearer. So that it will be easier for recognition steps. Machine learning systems provide machine recognition ability just like human beings.

The fundamental script in India is Brahmi. Such a significant number of works had been done in various Indian dialects except for Tulu, which is one among the various created types of Brahmi content [1]. The palm leaf original copy in figure 1(a) demonstrates the advancement of Tulu content since the twelfth century AD. Figure 1(b) shows a degraded paper document written in Tulu. The Tulu script, natively known as Tulu Lippi, is an alphabet used in the South Canara district of Karnataka, commonly for writing the Tulu, Kannada language and Sanskrit mantras in olden days. There are 48 letters in the Tulu content, each speaking to a syllable with the natural vowel/an/or/e/toward the finish of a sentence, which changes relying upon the diacritics around the letter. Pure Tulu can be composed of 35 consonant letters and 13 vowel letters. There are script-specific digits from 1 to 10 as shown in figure 1(c). Kannada is the dialect of Karnataka state for official work. Tulu speakers utilize the Kannada or Roman letters in order for official purposes. Tulu, Kannada alphabets [2] with ISO documentation is as appeared in figure 1(d). There are numerous family units in Tulunaadu of India with various documents written in Tulu content. The safeguarding of these reports in Kannada or roman editable frame gives significant understanding into previous history, societies, and civic establishments. Recognize the Tulu character in Kannada or roman editable form is the main intention of work.

For text recognition, firstly images of handwritten documents are pre-processed by removing noise and converting it to binary format. Binarization is fundamental so as to expel backdrop clatter and improve the lucidness. For uniquely identifying a character, its basic features should be extracted. The features may be its shape, size, etc. There are many methods available. After the feature extraction process, the character needs to classify based on the feature. The file written during feature extraction stage of the training process is opened in the testing process to compare test features of the input image. Deep CNN [3] and PNN models are used for classification of character images. In the PNN method, salient features of the characters are extracted using zone wise gradient direction values and applying wavelet transform. The gradient direction values and wavelet coefficients combined to form feature vectors which are then used for training the model. This is a significant stage as it's successful working improves the recognition rate and lessens the misclassification in accomplishing great execution of hand-written materials.

To evaluate the performance of system alphabets from Tulu palm leaf manuscripts and Tulu paper documents and Tulu numerals are considered. The work exhibited here included an adaptive thresholding based binarization, connected component analysis based division, skeletonization, Deep CNN and PNN based recognition. The related works are talked about in section 2.

Manuscript published on 30 June 2019.
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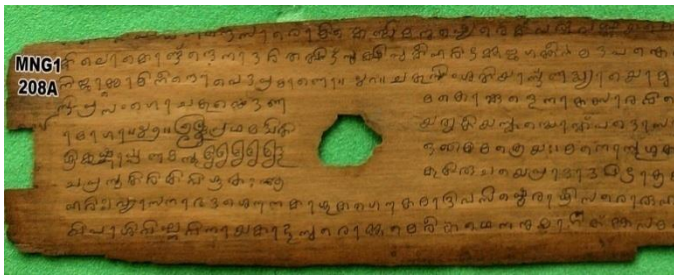
The proposed framework is clarified in section 3. Section 4 presents Implementation. Finishing up remarks are given in section 5.



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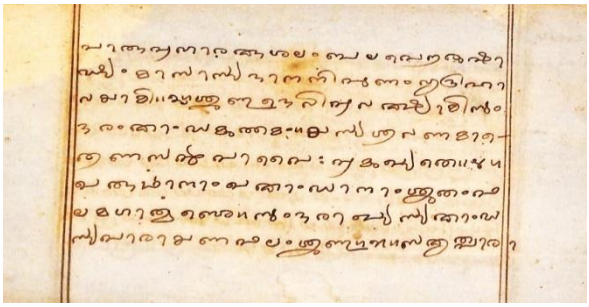

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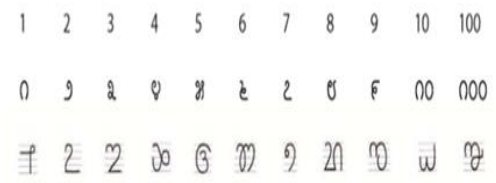

(c)

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(e)

Figure 1 (a) Tulu Palm leaf manuscript, (b) Tulu paper document (c) Tulu numerals (d), (e) Tulu, Kannada alphabets and ISO notation

II. RELATED WORK

The content extraction from the ineffectively debased record pictures is the inconvenient activity [4], attributable to the raised intra variety among the foreground and background text of assorted document pictures. Most of the thresholding based strategies are typically supported on a pixel gray level. Global thresholding method named Otsu thresholding based binarization is presented in [5], which results in poor binarization for degraded documents. Local thresholding methods binarization such as Niblack [6], its sliding window based nick thresholding techniques [7], Sauvola [8], etc are explained in survey paper [9]. Some methods combine features of different representation areas such as the spatial domain, frequency domain, etc. Filter based hybrid binarization approach is described in [10]. A strong combination could offer higher results. Advancement of Niblack's method, a Texture feature based binarization is presented in [11]. Promising results obtained by using texture descriptor based on the co-occurrence matrix. Robust historical document binarization using a histogram peak ratio is presented in [12]. Deep neural network based adaptive binarization approach is explained in [13]. The presented work proved a better result compared to Otsu's, Sauvola, etc. Document images include many lines, words, characters. Chutani et. al [14] proposed region localization based binarization with improved results by segmenting the proper region of interest.

Several approaches for character segmentation are proposed in [15]. Density estimation and level set based line segmentation approach are proposed in [16]. In [17] robust technique to segment, the text line is proposed using a convolution neural network. To handle lines written in different skew angles, adaptive, local projection profile based line segmentation technique is proposed in [18]. Split text lines and overlapping characters are handled and achieved 99.17% accuracy for Urdu Nastaleeq text [19]. Adaptive shock filter based denoising technique is proposed in [20]. After preprocessing image, there is a need for representation image with minimum features. Coded run method based feature extraction method is explained in [21] for recognition of Brahmi script. Sahlol [22] et. al proposed optimizers such as Grey Wolf Optimization (GWO) algorithm based feature extraction technique to recognize Arabic handwritten character. Histogram oriented gradient features based recognition system with an accuracy of 94.32% for Bangla handwritten characters are presented in [23]. A comparative study of texture feature sets such as wavelet transform, co-occurrence matrix, Gaber filter, etc is done in [24]. Authors concluded that Gabor filter approaches are more accurate compared to other techniques. The wavelet-based technique for recognizing single Chinese characters are presented in [25]. The classifier is used for recognition of 28 characters. 99.65% accurate recognition system is proposed using Convolution Neural Network in [26]. Here Density-based Clustering Algorithm is used for automated labeling of character. Chinese historical document recognition is presented in [27].

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Radical detection problem is addressed here properly with improved recognition rate. Offline character recognition survey is proposed in [28]. From the survey, it has been concluded that lack of proper noise elimination technique, representation of complex character only with statistical or structural information, classifiers which use large training time may reduce the performance of recognition system. So there is a need for proper preprocessing, feature extraction, classifier tool to recognize the character from all type of documents.

III. PROPOSED SYSTEM & RESULTS

The architectural design used to describe the methodology is built as in Figure 2.

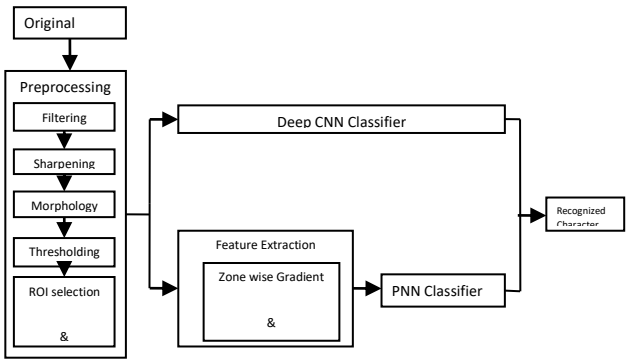
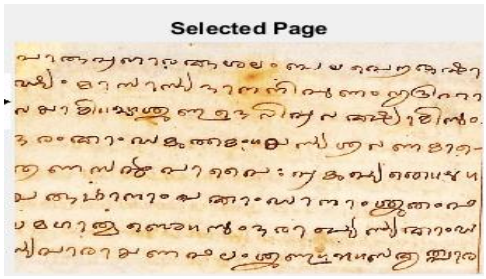


Figure 2 Proposed Architectural design

Image acquisition

Digitization is the formation of photographic pictures. The term is normally expected to infer the storage of pictures in digitized form. The image can be acquired in any of file format. Aquired input image of Tulu degraded paper document and part of palm leaf manuscript is as shown in figure 3(a) and 3(b).



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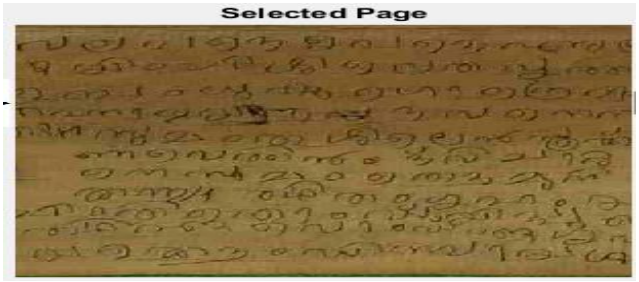

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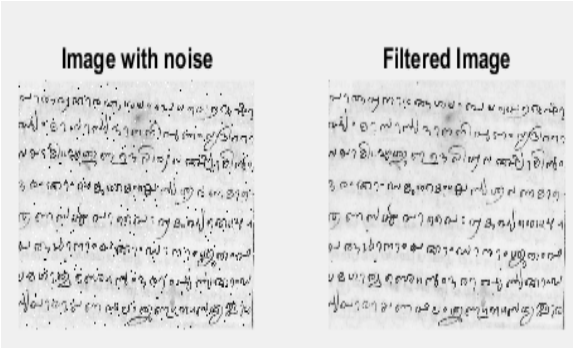
Figure 3 (a) Tulu degraded paper document (b) Part of palm leaf manuscript image

Image Pre-processing

The primary goal of preprocessing is to lessen degradations and variations in writing sorts of various human beings. The techniques utilized in preprocessing steps are greyscaled conversion, enhancement processes such as noise elimination using a median filter, sharpening the image, size normalization, edges detection, and binarization. 'Salt and Pepper noise' added to the input image and then filtered using the median filter as shown in figure 4(a) and 4(b). Sharpening the image is done using unsharp masking where edges of the images are sharpened and its histogram plot is shown in figure 4(c) and 4(d).

After enhancing the image, edges of images are detected by the Sobel method. It returns edges at those focuses where the slope of the picture is greatest. Then morphological operations such as dilation are performed on edges of image and IMFILL () function is used to fills holes in an intensity image. A hole is a territory of dull pixels encompassed by lighter pixels. Structuring element SE = STREL ('square', 2) used here to create a square structuring element. Adaptive threshold Binarization is performed as shown in figures 4(e) and 4(f).



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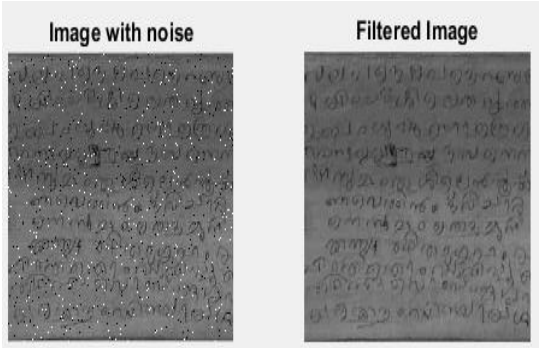

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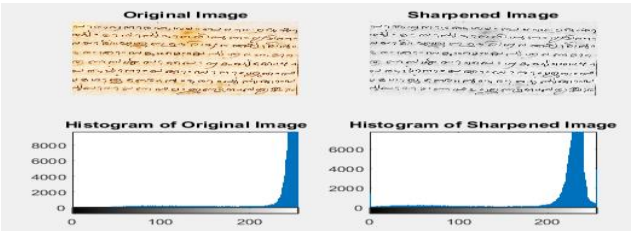

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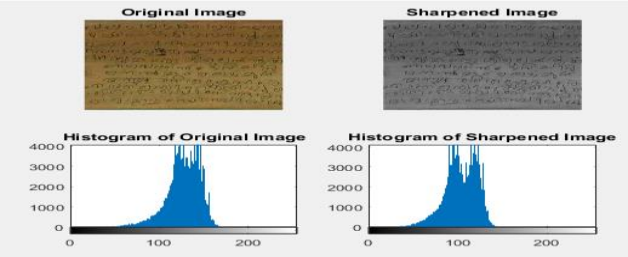

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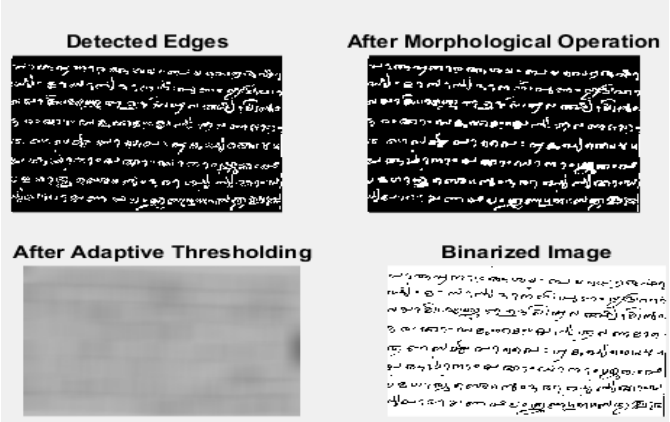

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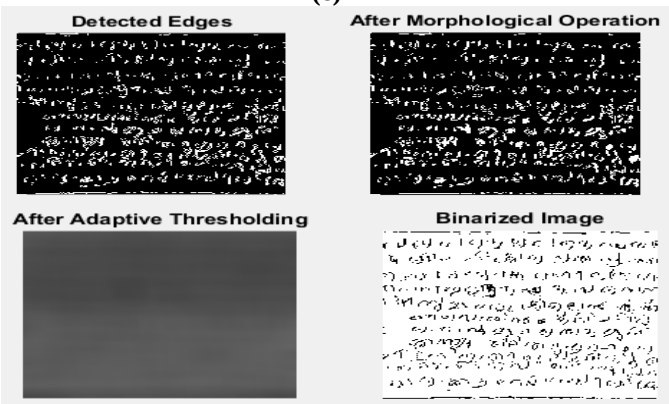
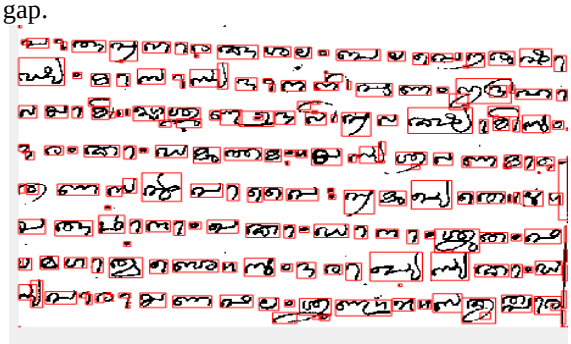


(f)

Figure 4(a) Filtered paper document image 4(b) Filtered palm leaf manuscript image 4(c) Sharpened paper document image and its histogram plot 4(d) Sharpened palm leaf manuscript image and its histogram plot 4(e) Adaptive threshold based binarized paper document Image after edge detection, morphological operations. 4(f) Adaptive threshold based binarized palm leaf manuscript Image after edge detection, morphological operations.

Segmentation

After enhancement of image, individual character is selected based on connected component analysis based region of interest selection (ROI) as shown in figure 5(a) and 5(b). Compare to, segmentation of the text of paper document pictures, the text segmentation from the poorly degraded pictures such as palm leaf image as shown in figure 4(f) is the troublesome job. Human intervention is needed here to select compound characters. In the case of palm leaf images, we can also perform segmentation of individual character, before binarizing image to obtain better results. Then adaptive thresholding with post-processing steps as explained in algorithm 1 is used to eliminate background noise as shown in 5(d). Finally, the skeleton of the image is constructed by the thinning process to represent a character image with minimum pixels. The skeleton of the character is as shown in the figures5 (c) and 5(d). Some skeletonized characters may be broken as in figure 5(d), which is identified based on the width of the connected component is below or equal to the mean threshold. Here threshold is measured as the ratio of the width of all character /Total character. The connected component with a smaller width is identified, then its endpoint is extended to connect endpoint of the nearest connected component to fill the gap.



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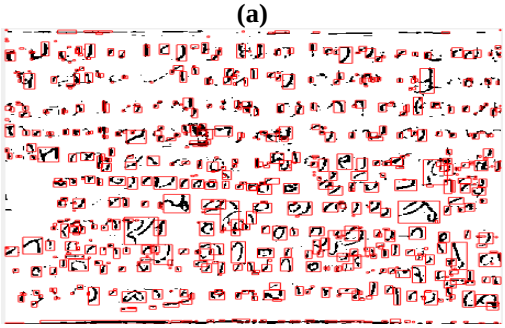

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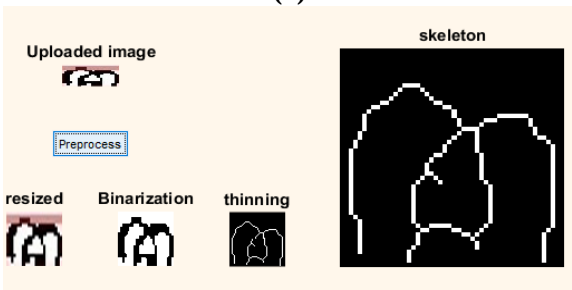

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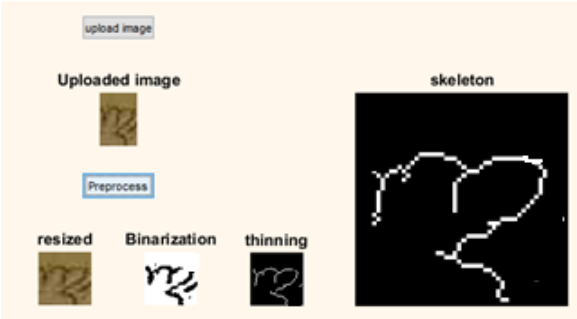

(d)

Figure 5(a) ROI selection of Tulu paper document image (b) ROI selection of Tulu palm leaf manuscript image. (c) Skeletonization of Tulu paper document image (d) Skeletonization of Tulu palm leaf manuscript image.

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Algorithm 1

Input: The isolated Palm leaf character Image I, Initial adaptive threshold binarized image B1, threshold value, mean threshold

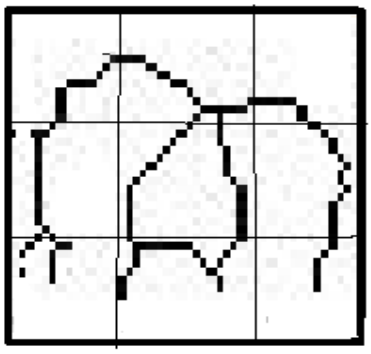
Ensure The Skeletonized result R1

1. Apply the Canny edge detector to detect edge pixels
2. Get the connected edge pixels by applying the connected component technique, Remove other isolated pixels.
3. For each resultant edge pixel(x,y), find four neighborhood pairs
4. Check the intensity of pixel value is below or above the threshold, if the adjacent pixel pairs belong to the same class
5. Assign pixel as text(1) if value is > threshold else assign pixel to background value (0)
6. Check if (width of connected component(CC)<mean threshold) then Imfill(CC)
7. end if, end if, end for
8. Output the new binary result B1 to skeletonization process.

Feature Extraction, Classification, and Recognition

In this stage, the highlights of the characters that are vital for grouping them at the recognition phase are separated. This is a significant stage as its powerful working improves the recognition rate and decreases the misclassification in accomplishing great execution of handwritten characters. The preprocessed image is taken for feature extraction. Features are nothing but visible characteristics. Two types of classifiers are used here for recognition.

i) The Probabilistic neural network classifier (PNN): It is a feed-forward system, which is broadly utilized in characterization and recognition issues. In a PNN, the activities are composed of four layers as information layer, concealed layer, design layer/Summation layer, yield layer. These systems are a lot quicker than multilayer perceptron organizes and can be more exact than multilayer perceptron systems. PNN systems are moderately uncaring toward anomalies. They can produce exact anticipated target likelihood scores. Bayes ideal grouping approaches are utilized in PNN. In order to train the PNN model, Zone based and Wavelet transform based feature extraction methods are used. Always combined feature extraction techniques give better accuracy compared to individual feature extraction techniques. The spatial domain is sufficient to extract structural information, but as the complexity of character increases, there is a need of extracting minute details by converting image into the spatial-frequency domain, which is achieved by applying wavelet transform. The structural features are extracted in a zone-based manner. Image is first converted to 3×3 matrix format. The zone selection is shown in figure 6(a). So, for a particular character, there are nine zones. The gradient direction of each zones is extracted. 12 Gradient directions give the change in the curvature direction. So, for each zone, 12 gradient directions are estimated. Like that there are 9 zones so total 108 gradient directions for an image. This 108 gradient direction values are taken as the feature values for a character.



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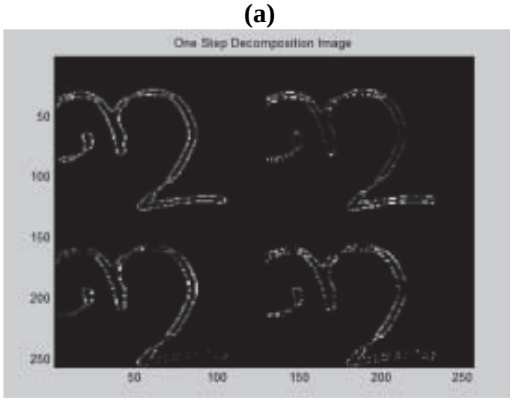

(b)

Figure 6(a). Zoning of Tulu Character (b) Decomposition of the image using wavelet transform.

Daubechies wavelet called dB4 can vigorously recognize features even among mess and under incomplete impediment, on the grounds that the wavelet highlights descriptor is invariant to uniform scaling, direction, enlightenment changes, and mostly invariant to relative mutilation. One stage decomposition of the picture by applying wavelet change is as in figure 6(b).

Wavelet coefficient values are first extracted for each character images. These features combined with extracted zonal features. This forms the final vector of features for every character and stored in the database. This feature extraction method is performed on each sample of each set of character and also on a test character. A character is perceived in a test picture by independently contrasting each element from the test picture to this database and discovering matching features dependent on the separations of their component vectors. In the PNN calculation, utilizing parent probability distribution function (PDF) of each class, the class likelihood of test input information is assessed and Bayes rule is then utilized to allow the class with the most elevated back likelihood to test input information. By this technique, the likelihood of misclassification is limited.

ii) The deep convolution neural network (Deep CNN):

Recently, 'deep artificial neural networks' have won various challenges. An 'Artificial Neuron Network (ANN)', prominently known as Neural Network is a 'computational model' dependent on the 'structure' and elements of natural neural systems.

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It resembles a counterfeit human sensory system for getting, preparing, and transmitting data. Essentially, there are 3 unique layers in a neural system as Input Layer (All the information sources are nourished in the model through this layer), Hidden Layers (There can be more than one concealed layers which are utilized for handling the sources of info got from the information layers), Output Layer (The information subsequent to preparing is made accessible at the yield layer). The Input layer speaks with the outer condition that shows an example to the neural system. This info gets exchanged to the hidden layers. The output layer of the neural system gathers and transmits the data as needs be in the way it has been intended to give. The example exhibited by the output layer can be legitimately followed back to the input layer. The number of neurons in the output layer ought to be straightforwardly identified with the kind of work that the neural system was performing. To speak to progressively complex highlights and to "adapt" progressively complex models for expectation and characterization of data that relies upon thousands or even a large number of highlights, we need ANNs somewhat more mind-boggling. This is practiced by basically expanding the number of hidden layers and/or the quantity of 'neurons per hidden layer'. More layers and more neurons can speak to progressively complex models, yet they likewise come at the expense of expanding time and power-devouring calculations. Such neural systems which comprise of multiple layers of neurons are called as 'Deep' ANNs and training them is called 'Deep Learning'. Deep systems can have upwards of 150 hidden layers. Deep learning models are prepared by utilizing huge arrangements of marked information and deep neural system structures that gain includes legitimately from the information without the requirement for manual component extraction. So here skeletonized pictures are given as sources of info. The low and middle dimensions of Deep ANNs extract the feature from the info picture. The last layer of Deep ANN utilizes a feed-forward neural system approach. Therefore, it is organized as a uniform system coordinated with every single fundamental module inside a solitary system. Hence, these system models regularly lead to better exactness contrasting and preparing of every module autonomously. In the event that the quantity of hidden layers turns out to be sufficiently huge, the Backpropagation calculation performs inadequately which is called reducing inclination issue. This issue happens in light of the actuality that the error signal decreases and littler, and it, in the long run, turns out to be too little to even consider updating loads in an initial couple of layers. This is the principle trouble amid the preparation of NNs approach. Deep learning has attempted its exceptional presentation within the ground of AI and pattern recognition from the most recent decade. Deep ANNs, as a rule, comprises of 'Deep Belief Network (DBN)', 'Stacked Auto-Encoder (SAE)' and 'Convolution neural system (CNN)'.We utilized a gradient-based learning calculation to CNN to perceive Tulu digits and Tulu letters in order. Here, the tasks are sorted out into a multilayered feedforward system with alternating convolution, max-pooling layers pursued by completely associated layer as appeared in figure 7. The softmax activation function is utilized in the 'output layer'.

Figure 7. Deep CNN Architecture

IV. EXPERIMENTAL STUDY AND ANALYSIS

To evaluate the ability of proposed method, the training database is provided with isolated character image is undergone through pre-processing steps such as enhancement; denoising and later the characters are binarized using adaptive thresholding technique and skeletonized. The letters of test documents are recognized using PNN and deep CNN models. Each model runs using parameter such as 'learning rate' and momentum. We have used modified parameters of VGG net architecture in Keras library using python programming, it was introduced in[3], which is characterized with alternating layers of 'convolution and max-pooling' layers to handle reduced volume size image. In VGG net, Softmax activation function is used along with 3 fully connected layers of 4096 nodes. We used the image size of 32X32 and since to find the best configuration of Deep CNN model, we have done an experiment by varying network size. From the experiment we find the value for learning rate is 0.01, the momentum of 0.1 and epoch set as 13 is best for getting high accuracy as shown in figure 8, which shows the best accuracy with respect to epochs.

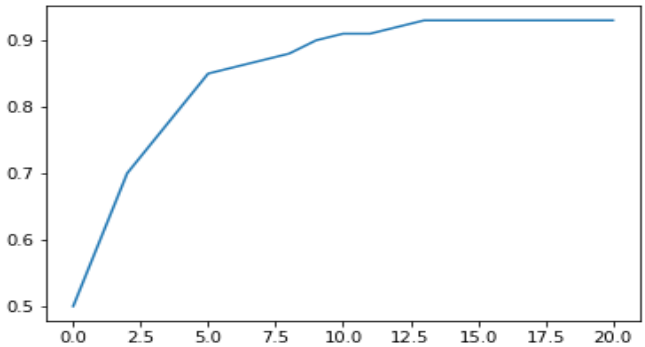

Figure 8 Accuracy versus Epochs plot

Performance evaluation is done based on metrics such as 'precision, recall, and accuracy'. 'Accuracy' is a proportion of the consequences of a test that figures the proportion of genuine anticipated qualities to all information. 'Precision' demonstrates the pertinence of information to the anticipated esteem. 'Recall' is a measure that expresses the measure of information pertinent to the deliberate information. Deep CNN engineering is chosen with Tulu character input picture, substituting convolution layer and a maximum pooling layer and a fully connected layer[29]. Final softmax layer neurons are reduced to 455 to represent different character classes of Tulu dataset. To evaluate the accuracy of the system for Tulu dataset, we considered 10 images of palm leaf manuscripts from Anathavatahra episode, 8 pages of paper documents from Ramayana, which are collected from the 'National.

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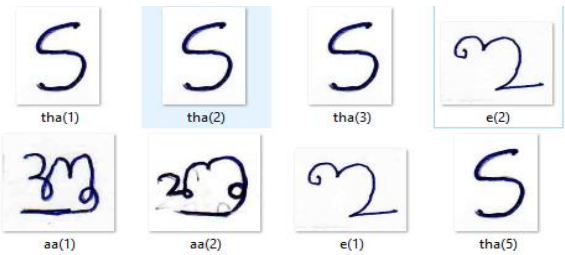
Trust for Computation and Archival of Oriental Media'. The documents are degraded due to various kinds of noises, including paper aging, ink stains, bleed through, paper crease, etc. We collected around 65 handwritten samples of 465 characters and 100 handwritten samples of Tulu numerals from native writers. This is the first methodology proposed on Tulu handwritten numerals. Each image in the datasets segmented using 'connected component analyses' to get isolated characters and resized into 32×32. To begin with we tried with Tulu numerals from 1 to 10; we got an accuracy of 98.12% using DCNN and 96.63% using PNN by considering only 10 character classes. For Tulu vowels, consonants, vowel diacritics with consonants, we totally generated more than 36,000 image patches which are labeled with the class label and stored as a database. Total 26,000 characters are trained, and 10000 characters are used as test dataset1. Highest accuracy of 93% is obtained using Deep CNN for test dataset1. We have considered 65 characters from palm leaf as test dataset 2.Overall accuracy of 88.07% is achieved for test dataset2 using Deep CNN. Figures 9(a) and 9(b) shows testing samples of isolated Tulu palm leaf characters as dataset1 and training samples collected on paper documents respectively. Handwritten Tulu numerals with its annotation are shown in figures 9(c) and 9(d) respectively. Figure 9(e) shows the editable representation of digits in Roman letters. Table 1 presents recognition efficiency for various categories of Tulu datasets. Recognition efficiency of palm leaf character images are reduced due to more degradation, unclear patterns compared to paper documents. Tulu character set consists of more than 300 characters and complexities of characters, the similarity between characters are more compared to roman characters. So that getting 100% accurate system is a difficult job. In the case of Tulu numerals, only 10 classes are considered. No much similarity between Tulu numerals except '3' and '6'.Only these digits are misclassified so that we got the highest accuracy in both the approaches. Deep learning approaches gives better results compared to other machine learning techniques.

(a)



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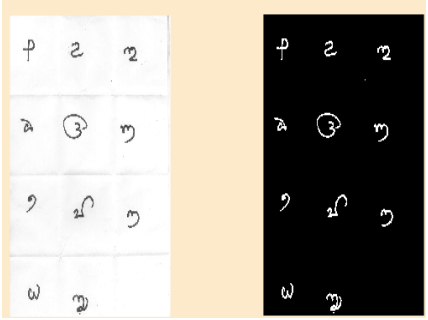
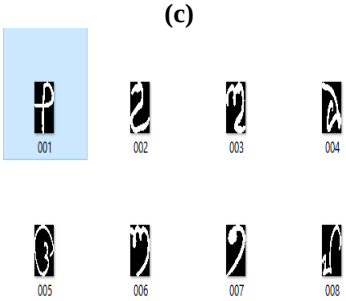
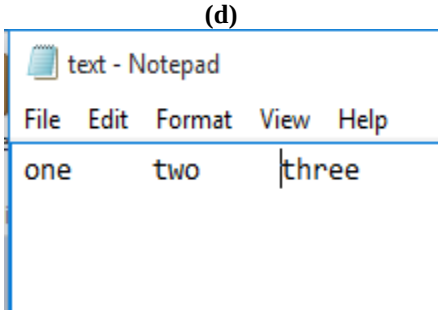


(c)



(d)



(e)

Figure 9 (a)Isolated Tulu palm leaf character images (b)Isolated Tulu character images from paper documents (c) Tulu numerals from 0 to 10 (d) Annotated numerals (e)Editable representation

Table 1 Performance evaluation of PNN and Deep ANN methods for various categories of Tulu datasets.

Sl. No	Dataset	Approach	Time in Seconds	Accuracy in %
1	Tulu Paper documents test dataset1	PNN	38.5	92.35
		DCNN	25.75	97.05
2	Tulu palm leaf characters test dataset2	PNN	40.5	86.12
		DCNN	32	88.07
3	Tulu numerals	PNN	30	96.93
		DCNN	22	98.12

CONCLUSION

Here we propose a method for handwritten character recognition on palm leaves manuscript images, paper document images and numerals of Tulu language, which is the oldest language of India.

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The proposed method deals with noise elimination, enhancement, and adaptive thresholding based binarization, skeletonization techniques with connected component analysis based segmentation of the image. Comparative study of two classifiers called PNN and Deep CNN are proposed here. In PNN, combined zonal and WT based 'feature extraction methods' are proposed to improve the 'accuracy' of recognition of palm leaf dataset to 86.12%. In Deep CNN, feature extraction is combined with classifier model, so that execution time is reduced to 32 seconds and better efficiency of the classifier is obtained compared to state of art methods available for recognition of palm leaf character images. The Deep CNN model outperforms compared to PNN and gives encouraging results to meet the objectives of handwritten Tulu character recognition system. This is the first proposal to recognize Tulu numerals.

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