Convolution Neural Network based Ancient Tamil Character Recognition from Epigraphical Inscriptions

M. Merline Magrina[1]

[1]Assistant Professor, Dept of ECE, Er.Perumal Manimakalai College of Engineering, Hosur, Tamilnadu, India.

---***---

Abstract - *Tamil is one of the oldest languages in the world with several million speakers in the Southern part of TamilNadu. Recognition of ancient Tamil characters is one of the challenging tasks of the epigraphers in the field of archaeology. More information is revealed by recognizing the characters inscribed on stones. Using OCR techniques the ancient Tamil characters between 9th and 12th century characters are recognized. Optical Character Recognition (OCR) is the process of converting the input images of text into a machine editable format. The important steps in OCR are pre-processing, segmentation & recognition. Deep Learning (DL) has been used in image classification, object tracking, face recognition, scene labeling, text detection, etc. Convolution Neural Network (CNN) is the most commonly used model in Deep Learning that has demonstrated high performance on image classification. In the present study, we performed certain amount of training of a 18 layers CNN for 73 class character recognition problem. This CNN architecture is trained towards the feature extraction of samples using ReLU activation function. CNN can automatically learn a unique set of features directly from the images in a hierarchical manner. Using our framework we achieved the Segmentation Rate & Recognition Rate as by mapping the. Ancient Tamil characters to Modern Tamil characters*

Key Words: **12th Century Tamil Characters, Bounding Box Technique, CNN Architecture, Softmax classification, Unicode mapping, Recognition rate.**

1. INTRODUCTION

Optical Character Recognition (OCR) is a research field in pattern recognition, artificial intelligence & computer vision. OCR is the process of mechanical/electronic conversion of printed text, images, scanned documents into machine editable format. Common methods of digitizing printed text to be electronically editable & widely used in machine learning process i.e. machine translation, text to speech and text mining. Early versions are to be trained with images of each character & worked on one font at a time. Advanced OCR is of two types namely Offline & Online character recognition (Fig 1).

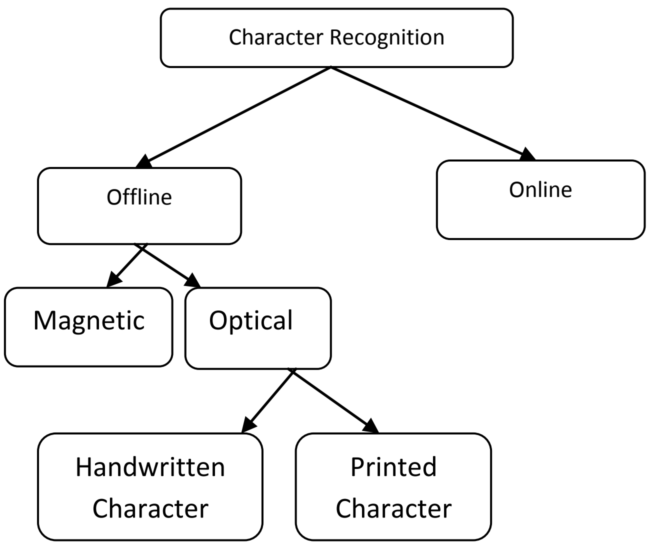

Fig 1: Types of Optical Character Recognition

Offline Character Recognition is an automatic conversion of text into image and then into codes that are usually used in computer & text processing application.

Online Character recognition deals with data stream which comes from a transducer while the user is writing. When the user writes on the tablet, the successive movements of the pen are transformed to a series of electronic signal which is analyzed by the computer.

OCR system undergoes following steps as shown in Fig 2 i.e. Pre-processing, Segmentation, Feature Extraction, Classification & Recognition of character.

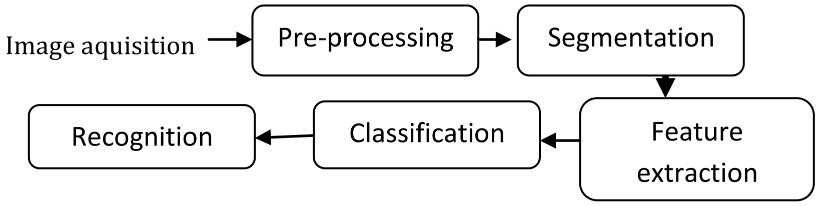

Fig 2:. Optical Character Recognition Steps

The field of Artificial Intelligence (AI) is essentially used when machines can do tasks that typically require human intelligence. It encompasses Machine Learning (ML) where machines can learn by experience & acquire skills without human involvement. Deep Learning (DL) is a type of ML in which a model learns to perform classification tasks directly from images, text, or sound. Deep learning is normally implemented using Neural Network architecture. The term “Deep” refers to the number of layers in the network i.e. more the layers, deeper the network. Traditional neural networks like ANN contains only 2 or 3 layers, while deep networks can have hundreds of layers. DL techniques have achieved top class performance in pattern recognition tasks. These include image recognition, human face recognition, character recognition & human pose estimation. The deep learning techniques have proved to outperform the traditional methods of pattern recognition. DL enables the automation of feature extraction tasks. The traditional methods involve the feature extraction through the manual methodology by applying the feature extractors. This task is time consuming but not very efficient. The effectiveness of the system purely depends upon the features extracted. Deep Learning methods outshine the traditional methods by automatic feature extraction.

Convolution Neural Network (CNN) is a popular deep learning method & is the state of the art for image recognition. CNN has achieved a breakthrough in the IMAGENET challenge 2011. The CNN used in the challenge was Alex-Net and gave an error rate of 16% in comparison to 25% in 2010. The properties of CNN are the local connectivity strategy & the weight sharing strategy. Convolution Neural Network is first introduced by LeCun, he developed a multilayer artificial neural network called LeNet-5 which can be widely used for the classification of handwritten numbers. Like other neural network, LeNet-5 has multiple layers & can be trained with the back-propagation algorithm. Because of the absence of substantial preparing information and processing power around then. LeNet-5 can't perform well on progressively complex issues like vast scale picture and video order. Since 2006, many methods have been developed to overcome the difficulties encountered in training deep neural networks. Krizhevsky proposed a classic CNN architecture AlexNet & showed significant improvement upon previous methods on the image classification task. With the success of AlexNet, several methods were proposed to improve its performance such as ZFNet, VGGNet & GoogleNet. In recent years, the optimization of CNN are mainly concentrated in the following aspects, the design of Convolution layer & pooling layer, the activation function, regularization & CNN can be applied to practical problems.

Recent studies on CNN have shown their power in recognition tasks. The CNN based acknowledgment approach has the successful favorable position of not requiring a hand-made component vector. This engineering is fit for taking in the component vector from the preparation character picture tests in an unsupervised way as in no hand-making is utilized to decide the element vector. This fact prompted us to study whether one can skip the pre-processing & feature extraction steps for character recognition of a new script for which it is possible to collect at least some training samples with ground truth. The proposed work assumes that there exists a CNN (Fig3) trained for sufficiently large character class problem.

Fig 3: Neural Network Architecture

The character inscribed on anything (stone) (Fig4) is called epigraphy. The study of ancient characters is called Palaeography. The characters were inscribed on palm scripts, stones, coins, mudkalangal, metals, beads & conch in ancient days have vital role in Tamil history. To know the Indian history completely many steps have been taken by the historians to inscribe their administrative operations on the stones & copper plates. It plays an important role in ancient periods. Testimonials are important for Historical formation. The historical loyalty is written only through epigraphical testimonials such as stone inscriptions and copper plate inscriptions which were given the first preference by the epigraphers. During Chola period the Brahmins were respected more but the low caste people were rejected still others were considered as untouchables. But the survey showed that Cholas showed social justice and their period is considered as Golden Period. From the stone inscriptions of Ashoka we came to know about the humanity, dharma & religious bouquets. These can be read from the stone inscriptions. The inscriptions can be from 1 to 100 lines and each inscription is considered as a historical significance of the Chola period and they remain as milestones in TamilNadu history. It is not easy to read the inscriptions on stones since they are written in the ancient Chola periods & it can be read only by practice. The medieval inscriptions were mostly in Tamil mixed with Grandha letters (Fig 5). Only if we know the Grandha characters we can be able to read the Tamil stone inscriptions completely. Archaeological departments of India and TamilNadu by their strong effort the Indian inscriptions were released and mostly they were transliterated in English and Devanagari scripts. There were some difficulties in reading those who know only Tamil so the Grandha scripts were transliterated & they are easily identified and read by the people about the explanations and testimonials in detail. The Historical documents can be read only by the experts in language, linguistics, literal & historical backgrounds. The historical documents can be easily understood by giving the basic knowledge and training about the inscriptions and more books must be published based on this. The inscription on the stone reveals the history, social and economical changes occurring in Tamil language and it can be understood from the testimonials.

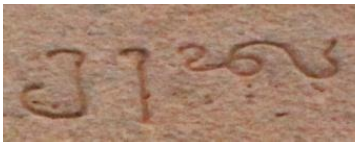

Fig 4: Stone Inscription

Fig 5: Grandha Script

Stone inscriptions are the characteristic evidence in the Tamil history which is the oldest period of about 2500 years. It plays an important role to know the history of the country through literature, archaeology and numismatics. If there are no inscriptions there is no TamilNadu History. “A complete history of India written today taking in to an account all recent epigraphic discoveries would be significantly different from and more complete than one written for example only 20 years ago, there is no reason to think that this pattern should change in the foreseeable future”. Most of the Tamil characters found in stone inscriptions in TamilNadu shown in (Fig 6) belong to the Chola’s, since they have ruled for about 4000 years and large number of stones was found in their period. 80% of the Tamil history was known only during the Chola period. Most of the inscription reveals not only the information about the temple & offerings but also their political history, administration, economics, village administration, land size methods & featured elements can be known. To know about VijayalayaChola, the stone inscriptions & copper plates found in Chola period became very important.

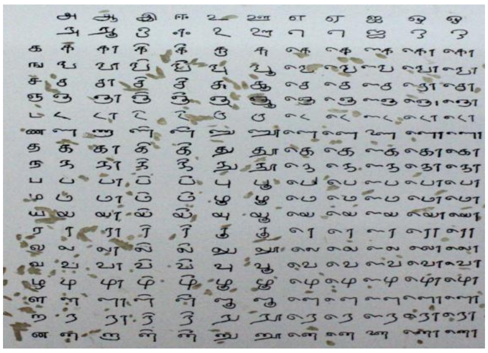

Fig 6: Characters found in Stone manuscript

International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 04 | Apr 2020 www.irjet.net p-ISSN: 2395-0072

1.1 Style of writing the inscriptions

Some special methods are followed in carving the inscriptions (Fig 7). In TamilNadu Tamil-Bhrami inscriptions, the letters are carved not on the smooth polished plain surface but on the coarse & rough surface of the stones. It becomes very difficult in reading those inscriptions and it has been improved & made easier in later days.

1. In the epigraphical stone inscriptions at the end of the sentence, there is no pulli like consonants.
2. Instead of using pulli at the end slash (\) is used.
3. Numbering the lines in the poem is followed in the poetic inscriptions.
4. The words are written in short forms eg. Samvathswara are written as samvath, samva, som.
5. There are mangala tags present at the starting of the inscriptions eg. Nandhi, lotus, conch, sivalingam has begun to take place.
6. The mistakes have been corrected at the time of carving.

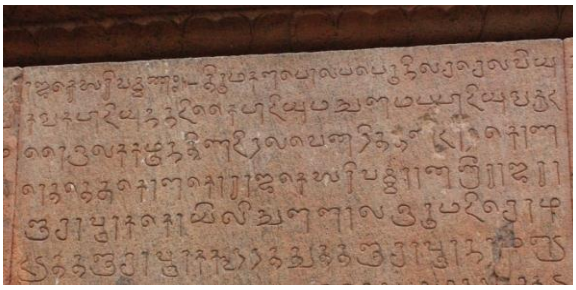

Fig 7: Sample stone manuscript

Explanation of the above stone manuscript

ராஜ தேவர்க்குயாண்ட திருமகள் போலப் பெருநிலைச்செல்வியு

கங்கபாடியு நீ தடிகை பாடியும் நுளம்பாடியுங் குட

ரை இலக்கழுந் திண்டிரல வெனரித் தளடார கொண்

ரெத் தெசு கோள் கோ ராஜ தேவர்க்குரான ஶ்ரீ ராஜ ரா

ஞ்சாவூர்க் கோயிலிநுள்ளால் இருமடி சோழ

டடுத் தஞ்சாவூர்க் கூற்ரத்துத் தஞ்சாவூர் நாம் எடு

1.2 Objectives

1. To recognize the characters by training the Convolution Neural Network architecture.
2. To map the characters using Unicode.
3. To test the variety of inscriptions & find the performance characteristics of the trained CNN network.

2. LITERATURE SURVEY

An introduction to classifiers and gradient-based learning is given and it is shown how several perceptrons can be combined and trained gradient-based. An overview of convolutional neural networks, as well as a real-world example is discussed [1]. the problems of the multilayer perceptron was shown, that the concept of convolutional neural networks and weight sharing not only reduces the need for computation, but also offers a satisfying degree of noise resistance and invariance to various forms of distortion. LeNet-5, as an application of convolutional neural networks, was shown to outperform most other techniques. With an error rate as low as 0.95% it is still a little bit more error-prone than the boosted LeNet-4. However, the requirement for extensive computation in boosted LeNet-4 makes LeNet-5 the perfect candidate for hand-written digit recognition.

An Tien Vo discussed that the image classification model applied for identifying the display of the online advertisement [2]. The proposed model uses Convolutional Neural Network with two parameters (*n, m*) where n is a number of layers and m is number of filters in Conv layer. The proposed model is called nLmF-CNN. The suitable values of parameters *(n,m)* for advertisement image classification are identified by experiments. The input data of the proposed model are online captured images. The processing components of nLmF-CNN are developed as deep neural networks using ConvNetJs library. The output of the proposed model is YES/NO. YES means that the advertisements display clearly. NO means that the advertisements do not display or not clear. The experimental results 86% in our normalizing dataset showed the feasibility of a proposed model nLmF-CNN.

Pranav P Nair proposed a system that uses Convolutional neural network to extract features. This is the method different from the conventional method that requires handcrafted features that needs to be used for finding features in the text. The network is tested against a newly constructed dataset of six Malayalam characters. The proposed method uses CNN to extract and classify Malayalam characters [5]. Both Sample generation and CNN modelling are time consuming tasks and the later also requires a CUDA enabled GPU for parallel processing. Preprocessing helps to remove the undesired qualities of an image and hence plays an important role in increasing the recognition task. So is the sample generation process that reduces overfitting. The drop out layer also reduces overfitting while also decreasing the overall training time. CNN has proved to be the state-of-the-art technique for other languages and hence provides the chance for giving higher accuracy rate for Malayalam characters and it can be used for office automation.

Qingqing Wang presented a hierarchical CNN model to recognize confusable similar handwritten Chinese characters [6]. This model inherits the hierarchical recognition idea from traditional methods, and takes the advantage of deep networks. Specifically, similar characters are classified into groups at first, and for each group, a special classifier is trained at next stage to capture the tiny difference of critical regions between similar characters. The proposed model has a parallel structure, the overall depth is relatively shallower, which means more tuning effort can be saved when comparing with the deeper network structure like AlexNet. Experimental results on 368 similar characters (detected from 3755 frequently used characters, and clustered into 172 groups) have shown that the proposed hierarchical CNN model is more effective and efficient than the existing work.

Tian Mei Guo discussed that the Convolutional neural networks demonstrates a high performance on image classification [7]. The work is based on benchmarking datasets minist and cifar-10. On the basis of the Convolutional neural network, different methods of learning rate set and different optimization algorithm of solving the optimal parameters on image classification are analyzed. This imposes less computational cost. The shallow network has a relatively good recognition effect is verified.

Wei Zhao proposed a superpixel-based multiple local convolution neural network (SML-CNN) model for panchromatic and MS images classification [8]. Superpixels are taken as the basic analysis unit instead of pixels. To make full advantage of the spatial-spectral and environment information of superpixels, a superpixel-based multiple local regions joint representation method is proposed. Then, an SML-CNN model is established to extract an efficient joint feature representation.

A softmax layer is used to classify these features learned by multiple local CNN into different categories. To eliminate the adverse effects on the classification results within and between superpixels, we propose a multi-information modification strategy that combines the detailed information and semantic information to improve the classification performance. The overall accuracy of the superpixel is 95.94% which is better than the pixel based system that achieves 93.58%.

Prashanth Vijayaraghavan et al. [10] proposed a handwritten character recognition system for Tamil characters using convolutional neural network. They augmented the ConvNetJS library for learning features by using stochastic pooling, probabilistic weighted pooling, and local contrast normalization get an accuracy of 94.4% on the IWFHR-10 dataset. Anitha et al [15] proposed Multiple Classifier System for Offline Malayalam Character Recognition. The features used are the gradient and density based features. The best combination ensemble with an accuracy of 81.82% was reported by using the Product rule combination scheme.

CAPTCHAs are used in many applications for machine and human identification [11]. Compared with traditional English and digital characters based CAPTCHAs, Chinese characters contain more complicated characters which greatly enhance the difficulty of automatic recognition. To solve that problem, we proposed a Convolution Neural Network (CNN) based approach. This approach greatly improves the recognition accuracy of Chinese Character CAPTCHAs with distortion, rotation and background noise. The experiment results show that this approach achieves more than 95% accuracy for single character and 84% accuracy for CAPTCHAs with four characters. Result indicates that deep neural network is useful in complicated structure of Chinese Character CAPTCHAs.

In the present study Durjoy Sen Maitra [12] performed certain amount of training of 5-layer CNN for a moderately large class character recognition problem. The architecture of CNN is trained for a larger class recognition problem towards feature extraction of samples of several smaller class recognition problems. In each case, a distinct Support Vector Machine (SVM) was used as the corresponding classifier. The CNN of the present study is trained using samples of a standard 50-class BangIa basic character database and features have been extracted for 5 different 10-c1ass numeral recognition problems of English, Devanagari, BangIa, Telugu and Oriya each of which is an official Indian script. Recognition accuracies are comparable with the state-of-the-art.

Handwritten Hangul recognition (HHR) remains largely unsolved due to the presence of many confusing characters and excessive cursiveness in Hangul handwritings [13]. The best existing recognizers do not lead to satisfactory performance for practical applications and have much lower performance than those developed for Chinese or alphanumeric characters. To improve the performance of HHR, here we developed a new type of recognizers based on deep neural networks (DNNs). DNN has recently shown excellent performance in many pattern recognition and machine learning problems. Hangul recognizers based on deep convolutional neural network is built and proposed several novel techniques to improve the performance and training speed of the networks. The performance of our recognizers on two public Hangul image databases, SERI95a and PE92 are systematically evaluated and a recognition rate of 95.96% on SERI95a and 92.92% on PE92 is achieved. The results yielded the improvements of 2.25 and 5.22% respectively on comparison with the previous best records of 93.71% on SERI95a and 87.70% on PE92. These improvements lead to error reduction rates of 35.71% on SERI95a and 42.44% on PE92, relative to the previous lowest error rates. This improvement fills a significant portion of the large gap between practical requirement and the actual performance of Hangul recognizers.

Rajakumar and Subbiah Bharathi [16] proposed a system to identify the characters of 7th century from Temple wall inscriptions based on feature extraction technique. The proposed system uses contour-let which handles the curved images exactly. Input characters are identified by clustering scheme and the noise is removed using fuzzy median filters. Finally system is evaluated by neural network for comparing the ancient characters with the modern characters.

Extracting textual information from natural images is a challenging problem with many practical applications [17].Unlike character recognition for scanned documents, recognizing text in unconstrained images is complicated by a wide range of variations in backgrounds, textures, fonts, and lighting conditions. As a result, many text detection and recognition systems rely on cleverly hand-engineered features to represent the underlying data. An unsupervised feature learning algorithm is used for low-level data representation where features are automatically extracted from the given data. The competitive results in both text detection and character recognition is achieved using a simple and scalable feature learning architecture incorporating very little hand-engineering and prior knowledge. These learned features are integrated into a large discriminatively-trained convolutional neural network (CNN). CNNs have enjoyed many successes in similar problems such as handwriting recognition, visual object recognition and character recognition.

3. METHODOLOGY

The recognition of Tamil characters from stone inscriptions from 12th century to 19th century has been concentrated to know the Chola period's culture & history of their dynasty. The way of digitizing the Ancient Tamil Characters to Modern Tamil Characters has been explained in this work. Using Convolution Neural Network (CNN) architecture & Unicode mapping the 12th century characters are trained and tested. The inscription images are collected from the TamilNadu Archaeological Department & 80% of images are treated as Training samples and 20% as Testing samples. The training samples are subjected to pre-processing & segmented into characters (Fig 8). The characters are applied to CNN architecture consists of 18 layers for feature extraction & classification through Softmax operator. The constructed architecture is trained & the testing samples are applied to the trained network and the exact classified character is mapped with the Unicode values & the Segmentation rate & Recognition rate is calculated.

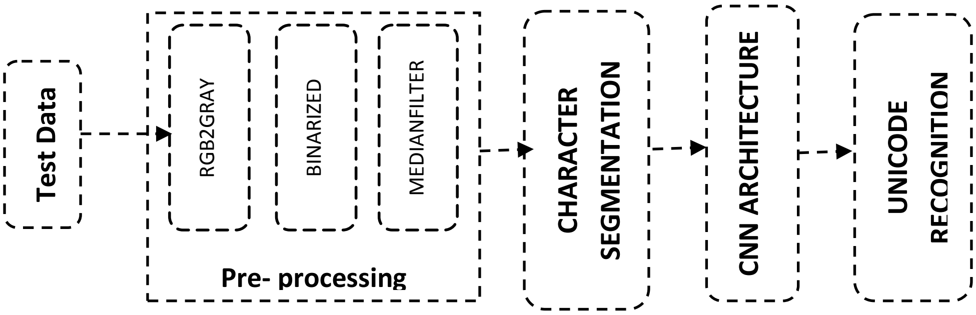

Fig 8: Proposed Block Diagram

Convolution neural network architecture

CNN is a type of artificial neural network used in image recognition & processing that is especially designed to process pixel data. It is a powerful image processing Artificial Intelligence (AI) that uses deep learning to perform both generative and descriptive tasks often it uses computer vision along with Natural Language Processing (NLP). Neural Network (NN) is not ideal for image processing and must be fed images in a reduced resolution. CNN has neurons that are responsible for image processing tasks. CNN is widely used tool in deep learning that is suitable for image processing. Layers of neurons are arranged in the way to cover the entire visual field avoiding the piecewise image processing problem. CNN system like a multi-layer perceptron designed for reduced processing requirement. CNN architecture consists of 3 layers namely Input layer, Hidden layer and Output layer as shown in the Fig 9.

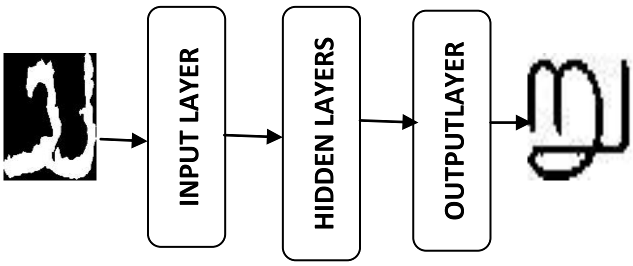

Fig 9: CNN Architecture

Layer Information:

Input Layer -1

It is a layer that accepts segmented character as an input image. That image is passed to the following hidden layers. The number of input layer is purely depends upon the task.

Hidden Layers -10

The hidden layers are responsible for feature extraction. The number of hidden layers is directly proportional to learning the features deeply. The accuracy of the system purely depends upon the training of the network. The number of hidden layer is 3 called mid-layers that each mid-layer consists of 4 CNN function layers namely Convolution layer, Activation layer, Normalization layer and Pooling layer and the last mid-layer consists of Fully-connected layer & pooling layer as shown in Fig 10.

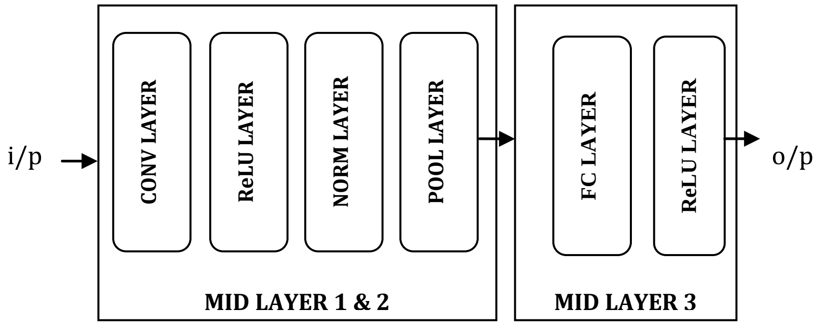

Fig 10: Hidden Layer Architecture

4. CONVOLUTION LAYER

The convolution layers serve as feature extractors and thus they learn the feature representations of their input images. The neurons in the convolution layers are arranged into feature maps. Each neuron in a feature map has a receptive field, which is connected to a neighbourhood of neurons in the previous layer via a set of trainable weights, sometimes referred as a filter bank. Inputs are convolved with the learned weights in order to compute a new feature map & the convolved results are sent through a non-linear activation function. All neurons within a feature map have weights that are constrained to be a equal, however different feature maps within the same convolutional layer have different weights so that several features can be extracted at each location. All the more formally the kth yield include map Yk can be processed as

$$Y_k = f(W_k * x)$$

where

x is denoted as input image

$\mathbf{W_k}$ is the convolution filter related to the k^{th} feature map

(*) is the 2D convolutional operator that used to calculate the inner product of the filter model at each location of the input image

f( ) is the nonlinear activation function that allows the extraction of nonlinear features.

5. RECTIFIED LINEAR UNIT (ReLU) LAYER

The most recent deep learning networks use rectified linear units (ReLU) for the hidden layers. A rectified linear unit has output 0 if the input is less than 0 & the output is equal to the input if the input is greater than 0. ReLU activation function is the simplest non-linear activation function. When the input is positive, the derivative is simply 1, so there is no squeezing effect met on the back- propagated errors from the sigmoid function.

$$f = \max(x, 0) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases}$$

ReLU is conventionally used as an activation function for the neural networks, with Softmax operator for classification problem. Such a network use the parameter called θ the Softmax function to learn the weight parameters of the network.

6. CHANNEL RESPONSE NORMALIZATION LAYER

A channel wise local response (batch channel normalization layer) carries out the channel wise normalization. This layer performs a channel wise local response normalization that follows the ReLU activation function. This layer replaces each element with a normalized value it obtains using the elements from a certain number of neighbouring channels. For each element x in the input, the trainNetwork computes a normalized value x' using

$$x' = \frac{x}{\left(k + \frac{\propto * ss}{windowchannelsize}\right)^{\beta}}$$

where k, α, β are the hyper-parameters in the normalization. ss is the sum of squares of the elements in the normalization window. The size of the normalization window is assigned using the window channel size function which is an argument in the cross channel normalization layer. The above mentioned parameters are user defined in nature.

7. POOLING LAYER

The next concept in CNN is pooling layer function that is a non-linear down sampling. There are several non linear functions to implement pooling commonly called Max-pooling. It partitions the input image into a set of non-overlapping rectangles for each sub-region, outputs the maximum value. The exact location of a feature is less than its neighbouring feature value. The pooling layer serves to reduce the spatial size of the representation, number of parameters, amount of computation & control the over-fitting. It is common to insert a pooling layer between the convolution layers. The pooling layer operates independently on every depth of the patches of input and resizes it spatially. The common form of the pooling layer with filters of size 2*2 applied with a stride of 2 down samples at every depth of the patches in the input by 2 along height & width discarding 75% of the activation function. This process is equivalent to fuzzy filtering. The pooling layer has the effect of the secondary feature extraction which can reduce the dimension of the feature map & increase the robustness of the feature extraction. The size of the feature maps in pooling layer is determined according to the moving steps of kernel. The max pooling function extracts the high level features of inputs by stacking the several convolution layers & pooling layers.

8. FULLY CONNECTED LAYER

The classifier of Convolution Neural Network is one or more fully connected layers. They take all neurons in the past layer and interface them to each and every neuron of current layer. There is no spatial information preserved in fully connected layers. The last fully connected layer is followed by an output layer. For classification tasks, Softmax operation is commonly used because it generating a probability distribution of the outputs. A fully connected layer multiplies the input by a weight matrix and then adds a bias vector that neurons represent the number of classes for the output layer.

Output Layers – 3

The extracted features are subjected to the output layer for classification process among 73 classes of the characters.

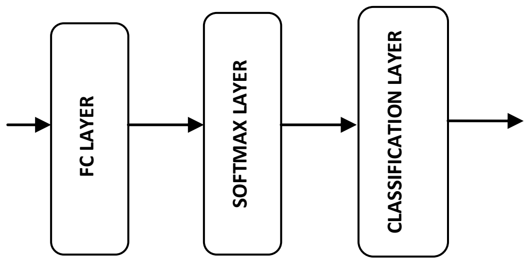

Fig 11: Output Layer Architecture

1. SOFTMAX LAYER

The sigmoid function can be applied easily, the ReLU activation function will not vanish the effect during the training process. Simply the sigmoid function can only applied to classify 2 classes, which is not applicable. The most popular classifier system used is Softmax Operator, which has a different loss function. The Softmax operator is the generalization of multiple classifiers. The outputs f (x_i, W) is a score for each class classification. In this classifier, the capacity mapping f (x_i, W)= Wx_i remains unaltered, yet we currently block these scores as the un-standardized log probabilities for each class and supplant the misfortune work with cross entropy misfortune work as

$$L_i = -\log\left(\frac{e^{f_{y1}}}{\sum_j e^{f_j}}\right)$$

where

f_j – j^{th} element of the vector of class scores f

L_i – overall training samples with the regularization term

$\frac{e^{f_{y1}}}{\sum_j e^{f_j}}$ - Softmax function

2. **CLASSIFICATION LAYER**

An arrangement layer processes the cross entropy misfortune for multi-class grouping issues with fundamentally unrelated classes. The layer derives the quantity of classes from the yield size of the past layer. For instance, to indicate the quantity of classes K of the system (73), incorporate a completely associated layer with yield estimate K and a Softmax layer before the grouping layer.

Recognition Model: Unicode Mapping emphasizes that each character code has a numerical value. Unicode text is simple to define & process. After classification the characters, they are recognized by Unicode. The exact character is mapped & the recognition rate is calculated.

$$Recognition\ rate = \frac{no\ of\ correctly\ classified\ characters}{total\ no\ of\ characters} * 100$$

Performance Measures

1. **Accuracy: Accuracy** is a measure of number of samples that are correctly classified.

$$Accuracy = {TP + TN}/{TP + FP + TN + FN}$$

where
TP= number of characters which are correctly assigned to the given category
TN= number of characters which are correctly assigned not to belong to category
FP= number of characters which are incorrectly assigned to the category
FN= number of characters which are incorrectly not assigned to the category

2. **F1_measure** is the calculation of performance of the classifiers.

$$F1\_measure = {2 * (Precision * Recall)}/{(Precision + Recall)}$$

where Precision (P) = TP/ (TP+FP) & Recall I = TP/ (TP+FN)
3. **Specificity =** TN/ (TN+FP)
4. **Sensitivity =** TP/ (TP+FN)
5. **Receiver Operating Characteristics (ROC)** is a comparison of the classification model that shows a trade off between TP & FP. The area under the ROC curve is a measure of accuracy. The model with perfect accuracy will be 1.0.
6. **Segmentation Rate:** The segmentation rate of the bounding box technology for segmenting the input into separate characters.

$$Segmentation\ Rate = \frac{no\ of\ correctly\ segmented\ characters}{total\ no\ of\ characters} * 100$$

9. EXPERIMENATAL RESULTS

The input Image is of dimension 284*114 is subjected to preprocessing steps for the removal of noises in the sample as shown in Fig 11.

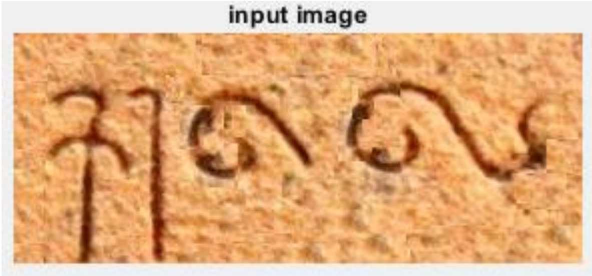

Fig11. Input image

The colored input image is binarized to remove noises present in the image as shown in Fig 12.

Fig12: Binarized Image

The noise free image is obtained by the post processing steps to highlight the background and foreground image i.e. character & background as shown in Fig:13.

Fig13: Dilated Image

Segmentation plays an important role character recognition problem. As the given input is word the best way to recognize the character is to separate each character as shown in Fig:14 using bounding box technique.

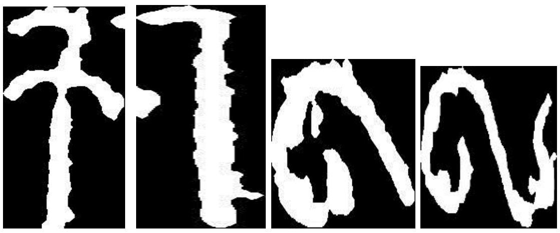

Fig 14: Segmented character

The segmented character's Gray image is applied for the constructed 14 layer CNN architecture whose training progress is given in Graphical model & Numerical values as shown in Fig 15 & 16.

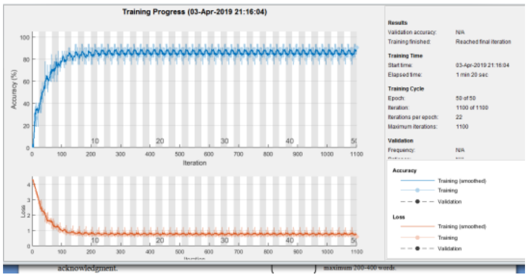

Fig 15: Graphical value of Training Progress

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch accuracy (%)	Mini-batch loss	Base learning rate
1	1	00:00:00	0.00	4.4125	0.0010
3	50	00:00:05	59.38	1.9116	0.0010
5	100	00:00:08	87.50	0.8958	0.0010
7	150	00:00:13	84.34	0.7996	0.0001
10	200	00:00:17	87.50	0.6224	0.0001
12	250	00:00:20	84.38	0.6496	1.000e-05
14	300	00:00:23	81.25	0.9323	1.000e-05
16	350	00:00:25	81.25	0.8905	1.000e-06
19	400	00:00:31	81.25	0.9758	1.000e-06
21	450	00:00:34	78.13	0.9534	1.000e-07
23	500	00:00:37	93.75	0.6450	1.000e-07
25	550	00:00:40	87.50	0.6284	1.000e-07
28	600	00:00:43	90.63	0.8522	1.000e-08
30	650	00:00:45	90.63	0.6447	1.000e-08
32	700	00:00:48	84.38	0.7401	1.000e-09
35	750	00:00:51	87.50	0.6051	1.000e-09
37	800	00:00:53	87.50	0.6430	1.000e-10
39	850	00:00:57	81.25	0.9330	1.000e-10
41	900	00:00:59	81.25	0.8898	1.000e-11
44	950	00:01:02	81.25	0.9753	1.000e-11
46	1000	00:01:05	78.13	0.9533	1.000e-12
48	1050	00:01:08	93.75	0.6450	1.000e-12
50	1100	00:01:11	87.50	0.6264	1.000e-12

Fig 16: Numerical value of the Training Progress

After training the network the subjected characters are classified correctly & recognized through Unicode as shown in Fig 17.

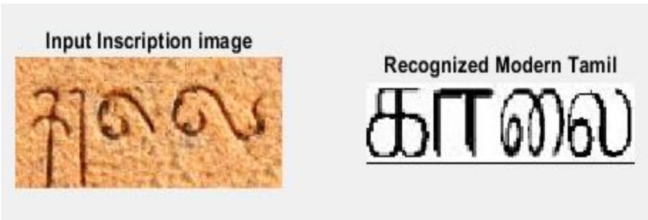

Fig 17: Recognized Modern Tamil Character

The recognition rate & segmentation rate is obtained through the trained network of the testing sample is shown in Fig 18.

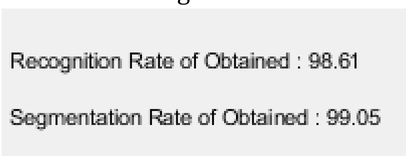

Fig 18: RR & SR of the recognized characters

The various performance measures calculated for the recognition of 12th century characters using CNN architecture is shown in Fig 19 & their respective values are discussed in Table 1.

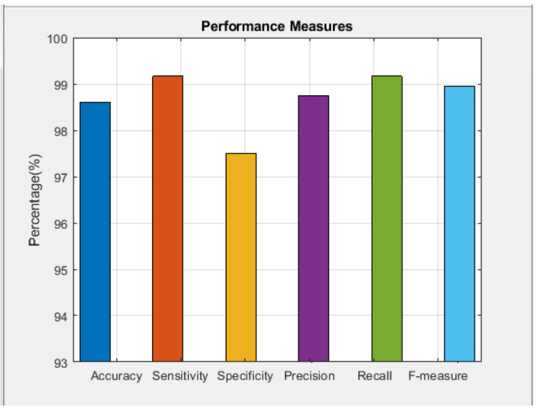

Fig 19: Performance Measures

Table 1: Performance Measures

Metric	Performance (%)
Accuracy	98.6092
Sensitivity	99.1649
Specificity	97.5000
Precision	98.7526
Recall	99.1649
F_measure	98.9583

Table 2: Confusion matrix

Confusion Matrix	Characters
TP	475
TN	234
FP	6
FN	4

The accuracy of the classifier is the tradeoff between TP & FP, the measure of the classifier accuracy is the curve that is shown in Fig 20.

ACCURACY : 97.50%

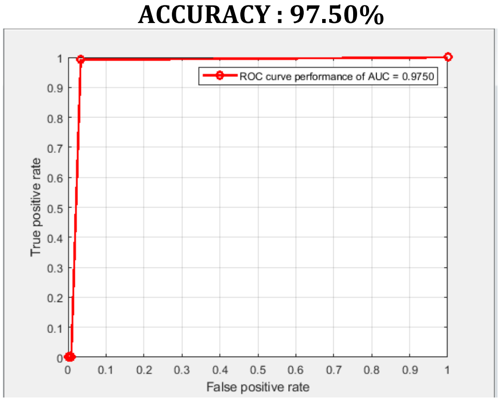

Fig 20: ROC Performance curve

10. CONCLUSION

Thus the proposed work focuses on Simple Convolution Neural Network for image classification which imposes a less computational cost. Researchers have been trying to increase the accuracy rate by designing better features using different classifiers. These attempts are limited when compared to CNN since it gives better accuracy rate. The results show that the CNN is capable of achieving good results on Tamil Dataset using a purely supervised learning. To simplify the work we did not use any unsupervised pre-trained network even though we expect that it will help. Our CNN has proved to be a state of the art technique for other languages and hence provides the chance for giving high Recognition rate of 98.61% and 99.05% Segmentation rate is obtained for Tamil characters.

ACKNOWLEDGEMENT

I owe my sincere thanks to **Dr. M. BHAVANI, Assistant Professor**, Department of Epigraphy & Archaeology, Tamil University, Thanjavur and **Mr. M. RAJENDRAN, Record clerk**, Department of Archaeology, Thanjavur who guided me and encouraged me to do the project in each and every step.

REFERENCES

[1] David Bouchin, "Character Recognition using Convolution Neural Networks", Statistical Learning Theory, Jan 2018, pg: 1-9.
[2] An Tein Vo, Hai Son Tran, Thai Hoang Le, " Advertisement Image Classification using Convolutional Neural Network", 9th International Conference on Knowledge and Systems Engineering (KSE), Oct 2017, pg: 197-202.
[3] Bhavani. B, "TamilNadu Historical Documents (Epigraphical Inscriptions)".
[4] Haifeng Zhao, Yong Hu, Jinxia Zhang, "Character Recognition via a Compact Convolutional Neural Network", International Conference on Digital Image Computing: Techniques & Applications (DICTA), Dec 2017, pg: 1-6.
[5] Pranav P. Nair, Ajay James, Saravanan C, " Malayalam Handwritten Character Recognition using Convolution Neural Network", International Conference on Incentive Communication and Computational Technology (ICICCT 2017), Mar 2017, pg: 278-281.
[6] Qingqing Wang, Yue Lu, "Similar Handwritten Chinese Character Recognition using Hierarchical CNN model", 14th IAPR International Conference on Document Analysis and Recognition, Nov 2017, pg: 603-608.
[7] Tianmei Guo, Jiwen Dong, Henjian Li, Yunxing Gao, "Simple Convolutional Neural Network on Image Classification", IEEE 2nd International Conference on Big Data Analysis (ICBDT 2017), Mar 2017, pp: 721-724.
[8] Wei Zhao, Lincheng, Jiao Wenping Ma, Xianghai Cao, "Superpixel based Multiple Local CNN for Panchromatic & Multispectral Image classification", IEEE Transactions on geo-science and remote sensing, Apr 2017, vol:55, pg: 4141-4156.
[9]Xuefeng Xiaoa, Lianwen Jina, Yafeng Yanga, " Building fast and compact Convolutional Neural Networks for Offline Handwritten Chinese Character Recognition", Elesevier, Feb 2017, vol:72. pg: 72-81.
[10] Prashanth Vijayaraghavan, Mishra Sra, "Handwritten Tamil Recognition using a Convolution Neural Network", International Journal of Computer Science & Technology (IJCST 2016), pg:1-7.
[11] Yanping Lv, Feipeng Cai, Dazhen Lin, "Chinese Character CAPTCHA Recognition based on Convolution Neural Network", IEEE Congress on Evolutionary Computation (CEC), pg: 4854-4859.
[12] Durjoy Sen Maitra, Ujjwal Bhattacharya, Swapan K. Pauri, "CNN Based Common Approach to Handwritten Character Recognition of Multiple Scripts", 13th International Conference on Document Analysis and Recognition (ICDAR 2015), Nov 2015, pg: 1021-1025.
[13] In Jung Kim, Xiaohaui Xie, "Handwritten Hangul Recognition using Deep Convolution Neural Networks", International Journal of Document and Analysis (IJDAR 2015), Sep 2014, vol:18, pg: 1-13.
[14] Prabhavathi, Karthikeyan, "Eighth Century Tamil Character Recognition", International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE 2015), Apr 2012, vol: 3, issue: 5, pg: 707-712.
[15] Anitha Mary, Chacko and Dhanya (2014), "Mutiple Classifier System for Offline Malayalam Character Recognition", International Conference on Information & Communication Technologies, Dec 2014, vol: 46, pp: 86-92.
[16] Rajakumar. S and Subbaiah Bharathi .V (2012), "7th Century ancient Tamil character Recognition from Temple Wall inscriptions", International Journal of Computer Science & Technology, Nov 2102, vol: 5, issue: 3, pp: 673-677.
[17] Tao Wang, Andrew Y. Ng, "End to end Text Recognition with Convolution Neural Network", IEEE International Conference on Pattern Recognition (ICPR 2016), Nov 2012, pg: 3444- 3449.