Handwritten Character Recognition of Tamil Font

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Introduction

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- Need to develop handwritten character recognition system for a rich and cultured language of Tamil, since not much work is done previously with considerable accuracy.
- We propose Deep and Machine Learning approaches for the same to achieve more accurate results.

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- Vijayaraghavan and Sra(2015), achieved an accuracy of 94.4% using CNN with 35 classes.

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- It gives much better accuracy compared to other unsupervised learning approaches(Described later).

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- Artificial Neural Networks

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- Convolutional Neural Networks

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- Future Scope and Improvements

Introduction to Optical Character Recognition(OCR)

Different areas of Character Recognition

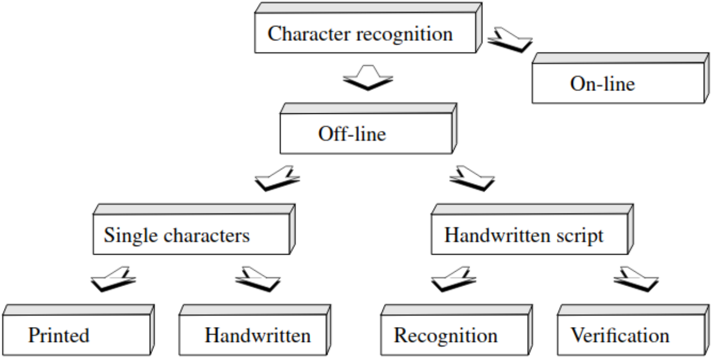

Figure: Different areas of Character Recognition.

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  - Recognition of the characters

OCR system components

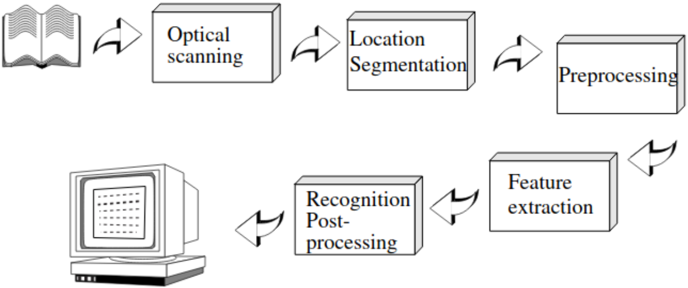

Figure: Typical OCR system components.

Neural Networks

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- Each neuron is connected to thousand of neurons and simultaneously receiving and sending multitude of these spikes.

Biological Neuron

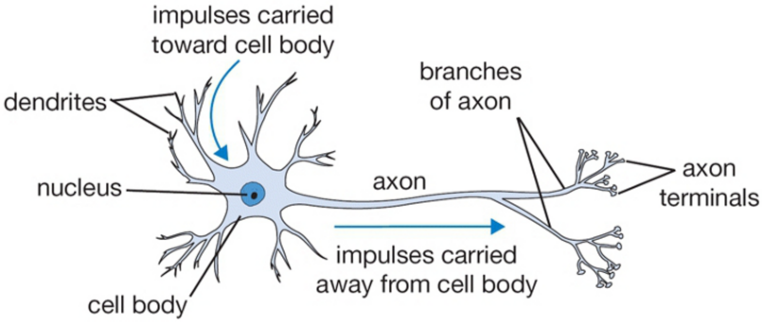

Figure: A Biological Neuron.

Artificial Neuron

- An artificial neuron assigns weights to all the inputs it receives and applies an activation function, f, to the weighted sum of the inputs along with some bias.

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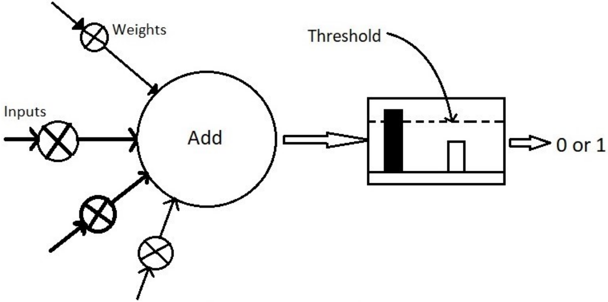

Figure: An Artificial Neuron.

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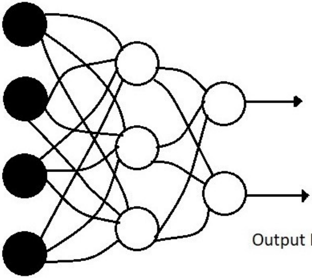

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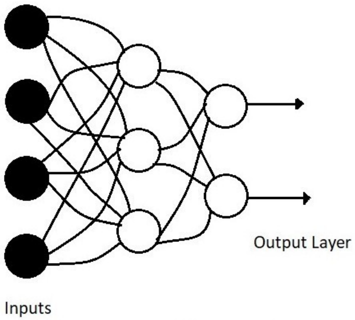

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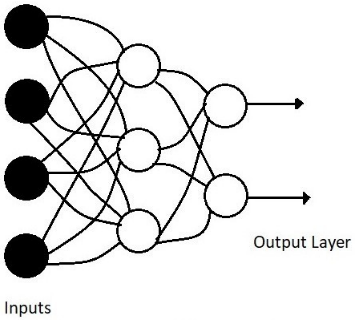

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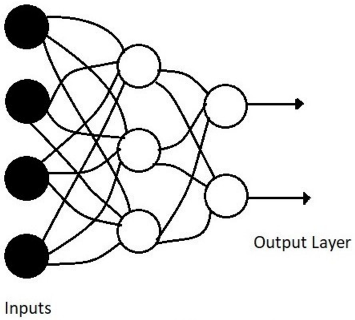

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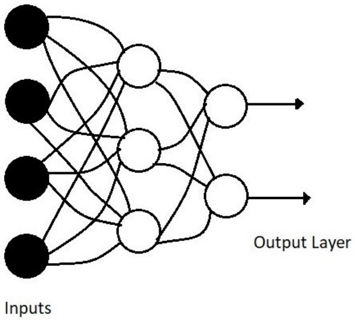

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  1. **Single Layer Perceptron**
  2. **Multi Layer Perceptron**

This model contains a single input neuron without any hidden layer.

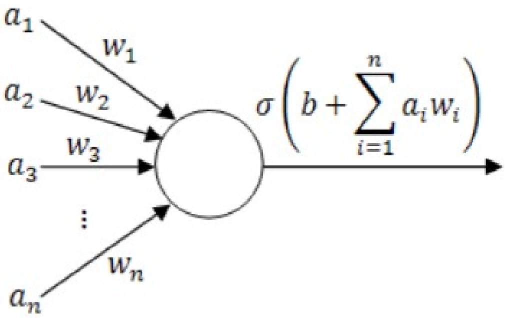

Figure: A Single-layer Perceptron.

Multiple-Layer Perceptron

This type of network contains multiple layers interconnected in a Feed-forward manner.

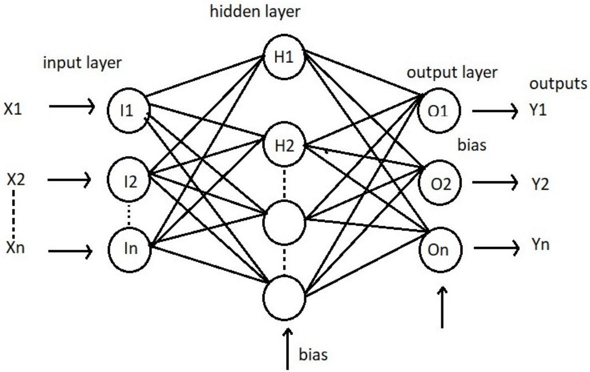

Figure: Multiple-Layer Perceptron

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Convolutional Neural Networks(CNN) comes under supervised learning.

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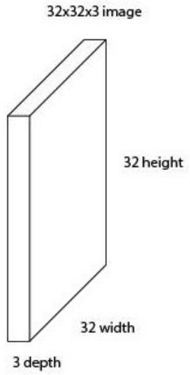

Why is it better?

- CNN uses the concept of weight sharing
- There is a reduction in the number of parameters
- It doesn't suffer from *overfitting* and hence improved generalization
- It is much easier to implement large models in CNN

CNN Architecture

CNN model consists of three types of layers -

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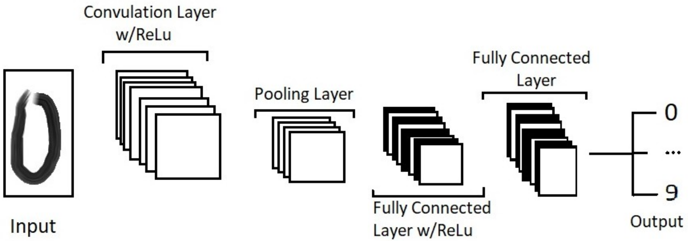

Figure: Layers of CNN.

Functioning of CNN

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- Fully Connected Layer performs actions that are performed in the general Neural Network model.

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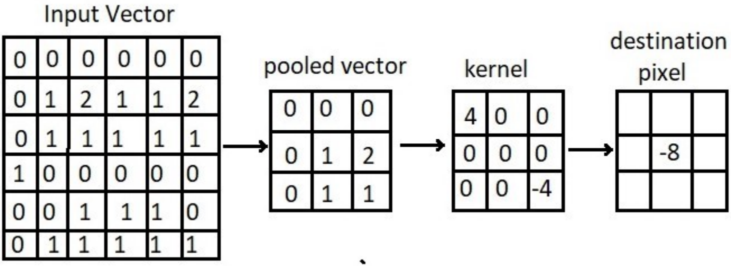

Figure: Representation of Convolutional Layer.

Convolutional Layer

Output can be optimized by tuning these hyper-parameters in Convolutional Layer :-

- Depth

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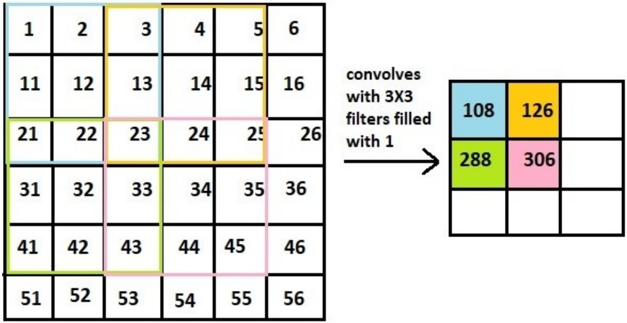

Figure: When stride is set to 2.

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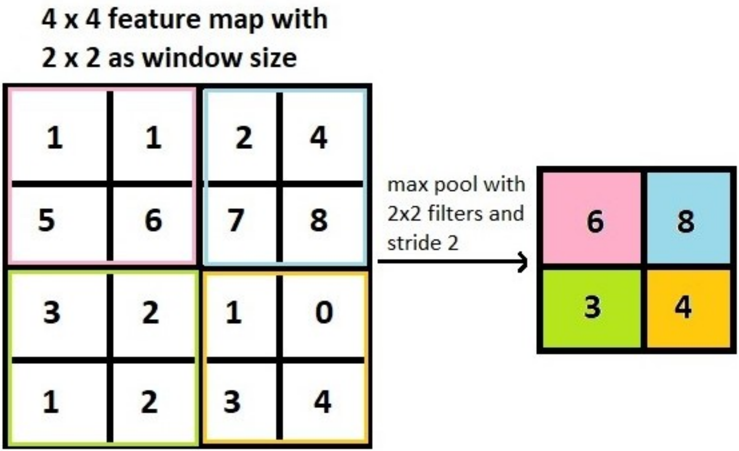

Figure: Max Pooling

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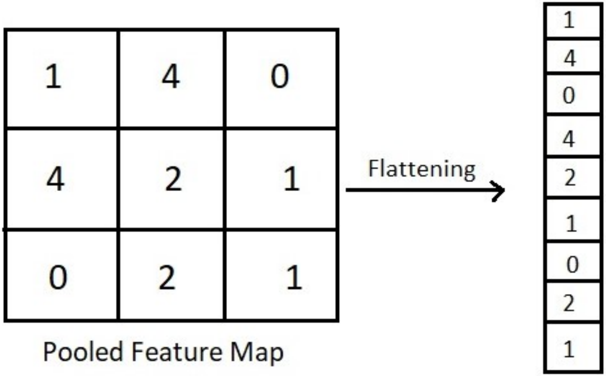
- Before it, flattening of the input matrix needs to be performed.

Flattening



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- ReLu is used as activation function between these layers.

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$$w(t) = w(t-1) - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

Image Pre-processing and Model Architecture

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- It contains 156 characters of Tamil script.
- Around 480 samples of each of the characters.
- Data is available in raw form, so we need to process the images.

Tamil vowels and consonants

Tamil vowels and consonants , with combinations of vowels and consonants.

Vowels	Consonants	Consonant + vowels	Compound Characters
அ	க்	க்+அ	க
ஆ	ங்	க்+ஆ	கா
இ	ச்	க்+இ	கி
ஈ	ஞ்	க்+ஈ	கீ
உ	ட்	க்+உ	கு
ஊ	ண்	க்+ஊ	கூ
எ	த்	க்+எ	கெ
ஏ	ந்	க்+ஏ	கே
ஐ	ப்	க்+ஐ	கை
ஒ	ம்	க்+ஒ	கொ
ஓ	ய்	க்+ஓ	கோ
ஔ	ர்	க்+ஔ	கௌ
	ல்		
	வ்		
	ழ்		
	ள்		
	ற்		
	ன்		

Figure: Tamil script characters

Characters in the Data-set

The 156 characters are encoded as labels numbering from '0-155' in the same sequence in which they are encoded

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						

Figure: HP Labs Tamil Data-set

Training and Testing of model

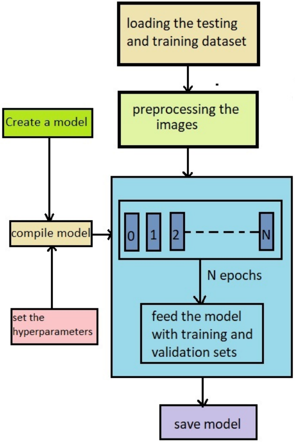


Figure: Proposed Model

Image Pre-processing

- Image Resizing (Bilinear Interpolation)

Image Pre-processing

- Image Resizing (Bilinear Interpolation)
- Image Smoothing

Image Pre-processing

- Image Resizing (Bilinear Interpolation)
- Image Smoothing
- Colour Inversion

Image Pre-processing

- Image Resizing (Bilinear Interpolation)
- Image Smoothing
- Colour Inversion

Bilinear Interpolation

$$g(n_1, n_2) = A_0 + A_1 n_1 + A_2 n_2 + A_3 n_1 n_2$$

Model Architecture

- CNN model for our HTCR system consists of 10 layers -
    - 4 Convolutional Layer

Model Architecture

- CNN model for our HTCR system consists of 10 layers -
  - 4 Convolutional Layer
  - 4 Max Pooling Layer

Model Architecture

- CNN model for our HTCR system consists of 10 layers -
    - 4 Convolutional Layer
    - 4 Max Pooling Layer
    - 2 Fully Connected Layer

Model Architecture

- CNN model for our HTCR system consists of 10 layers -
  - 4 Convolutional Layer
  - 4 Max Pooling Layer
  - 2 Fully Connected Layer

We perform Batch normalization after every Convolution Layer.

Model Architecture

- ReLu activation function is used in each Convolutional Layer .

Model Architecture

- ReLu activation function is used in each Convolutional Layer .
- Input Layer is composed of sample images of 64×64 .

Model Architecture

- ReLu activation function is used in each Convolutional Layer .
- Input Layer is composed of sample images of 64×64 .
- The Output Layer is composed of a **softmax** classifier with 156 labels.

Model Architecture

- ReLu activation function is used in each Convolutional Layer .
- Input Layer is composed of sample images of 64×64 .
- The Output Layer is composed of a **softmax** classifier with 156 labels.
- First two Convolution Layers have filter set to 32 and next two have filter set to 64.

Model Architecture

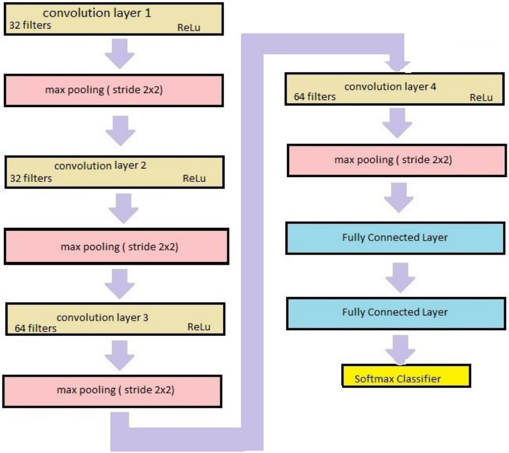


Figure: Model Architecture

Hyper-parameters

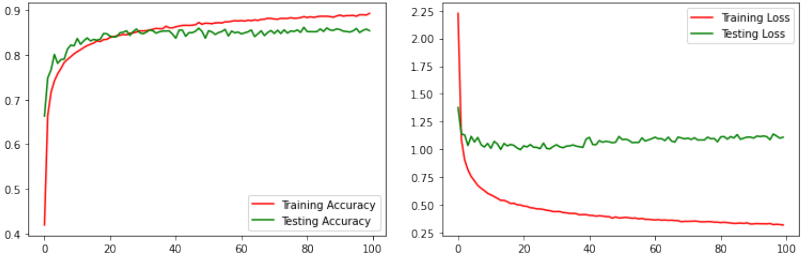
Hyper-parameters	Values
Batch Size	64
Initialization	Xavier
Optimizer	Adam
Epochs	100
Activation function	ReLu
Learning rate	0.001

Experiment

- *ImageDataGenerator* function is used to import input images to the environment
- In the first experiment, we use batch size of 32
- Image dataset is the same but with the dimensions 32×32

No of epochs	100
Batch Size	32
Total parameters	93,244
Trainable Parameters	92,476
Non-trainable Parameters	768
Training Loss	0.3174
Training Accuracy	0.8934
Testing Loss	1.1097
Testing Accuracy	0.8546

Results of 1^{st} experiment

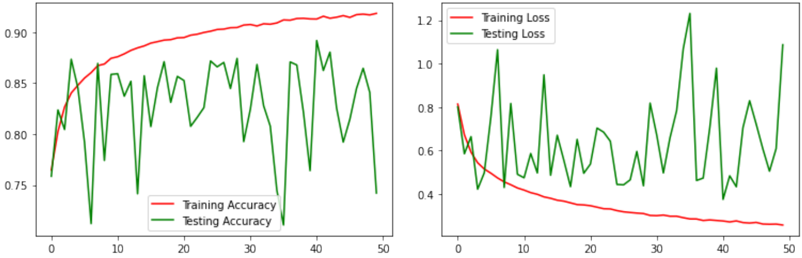


2^{nd} Experiment Results

- In the 2^{nd} experiment, we use batch size of 64
- Image dataset is the same but with the dimensions 64×64
- Number of epochs was set to 50 only because of computational constraints

No of epochs	50
Batch Size	64
Total parameters	158,780
Trainable Parameters	158,012
Non-trainable Parameters	768
Training Loss	0.2569
Training Accuracy	0.9285
Testing Loss	1.0871
Testing Accuracy	0.7421

Results


0.90
0.85
0.80
0.75
0 10 20 30 40 50
Training Accuracy
Testing Accuracy
1.2
1.0
0.8
0.6
0.4
0 10 20 30 40 50
Training Loss
Testing Loss

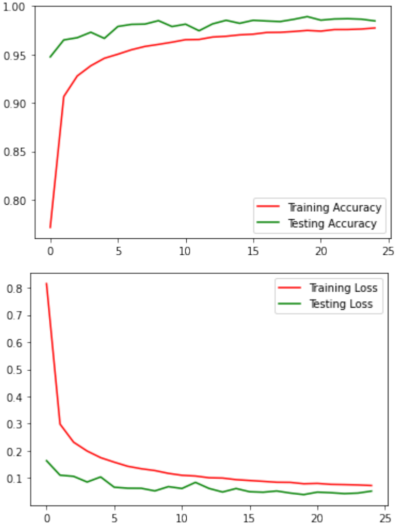
Same model on Devnagri Script (3^{rd} experiment)

- We have a vast set of data for Devnagri available online
- Number of labels are changed to 56
- Total 2000 samples, split into 1700 images for training set and 300 for validation set
- Number of epochs is set to 100 here as well.

Results

No of epochs	100
Batch Size	32
Total parameters	86,094
Trainable Parameters	85,326
Non-trainable Parameters	768
Training Loss	0.0724
Training Accuracy	0.9774
Testing Loss	0.0520
Testing Accuracy	0.9847

Results



1.00
0.95
0.90
0.85
0.80
Training Accuracy
Testing Accuracy
0
5
10
15
20
25
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
Training Loss
Testing Loss
0
5
10
15
20
25

Comparison of Results

Comparing the results of all three experiments:-

Parameters	1^{st} exp	2^{nd} exp	3^{rd}exp
Batch Size	32	64	32
Training Loss	0.3174	0.2569	0.0724
Training Accuracy	0.8934	0.9285	0.9774
Testing Loss	1.1097	1.0871	0.0520
Testing Accuracy	0.8546	0.7421	0.9847

Future Scope & Further improvements

- Increase the number of samples available per characters.
- Improved pre-processing of the sample images from the data-set
- Development of automatic feature extraction methods and combine them with the proposed model.
- Not considering all characters of Tamil font because of lack of Data-set, we propose to apply the model to all the characters of Tamil script.

References

O'Shea Keiron, Ryan Nash et al, 2015
Introduction to convolutional neural networks
Research Gate', 15th December, 2015.

Kevin Gurney[1997]
An introduction to neural networks
CRC press,1997

BR Kavitha and C Srimathi[2019]
Benchmarking on offline handwritten tamil character recognition using convolutional neural networks.
Journal of King Saud University-Computer and Information Sciences,20190

Sakshi Indolia, Anil Kumar Goswami, SP Mishra, and Pooja Asopa[2018]
Conceptual understanding of convolutional neural network-a deep learning approach.
Procedia computer science,132:679-688,2017

HP Labs Tamil-Character Data-set
http://lipitk.sourceforge.net/datasets/tamilchardata.htm

The End