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Linguistech A Cursive Handwriting Recognition System

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Abstract – In computer vision, recognition of alphabets and digits is a difficult and challenging task. Handwriting and alphabet recognition has its own importance within the field of bank cheques, American postcard, medical prescription letter, government sectors, etc. The complexness of recognizing alphabets lies within the stroke, inclination, size and the different handwriting styles. LINGUISTECH identifies the text presented to the machine by utilizing the principles of machine learning and artificial intelligence. Artificial Intelligence can be said to be as the perception of the environment and to act on the particular environment intelligently. Neural networks is one of the tools of Artificial Intelligence. Neural networks has improved the artificial computing and experience of science for optical character recognition. The system can be used to recognize the English characters (A-Z, a-z),numerals(0-9) and special characters(#,$,%,^,&,*).The process is implemented using Convoluted Neural Network(CNN) algorithm. Convolutional networks were inspired by biological processes in which the connectivity pattern between neurons is inspired by the organization of the animal visual cortex. CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage. We are aiming to implement the system for free handwritten characters, numerals and special characters along with a comparative study on various algorithms and its efficiency.

Index Terms – Artificial Intelligence, Convoluted Neural Network, Handwriting Recognition, Machine Learning.

1. INTRODUCTION

The recognition of handwritten text encompasses the process of converting handwritten characters into an editable digital format. The system makes use of machine learning algorithms and artificial intelligence tools to predict the handwritten text and convert it into the corresponding ascii format. While handwritten documents have hitherto been typed manually to maintain a digital version of the same the implementation of this system enables users to convert handwritten text to a text file by simply plugging it to the proposed system. This system makes life easy for various use cases which spend time and money on such a translation by hiring a typist such as doctors prescriptions, government documents etcetera. Thus, the implementation of this system takes the current trend of automation one step further. The system takes in the scanned image of text written in cursive handwriting. Then segmentation of text into distinct characters occurs. The required features are extracted from the characters and cursive strokes are processed. Then the neural network is trained by collecting handwriting samples and creating a dataset which is fed to the neural network. The neural network then matches the trained data with input to predict the character and displays its digital equivalent in a text file which can be edited.

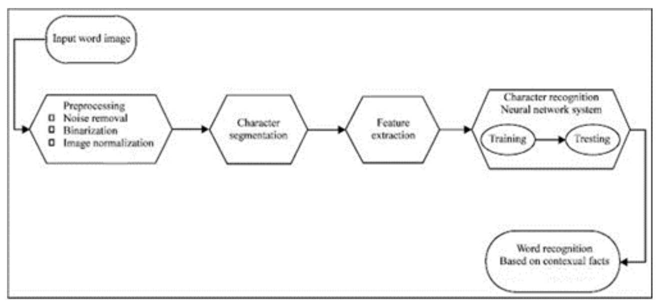

Fig.1. System architecture

2. EXISTING AND PROPOSED SYSTEM

A. Existing System and its disadvantages

The recognition of cursive texts based on division of continuous characters in triplets was proposed in 1999. A word was segmented into triplets and subsequent triplets contained two common letters. It was observed that recognition rates were higher when the characters were overlapped.

Horizontal/Vertical strokes along with Zoning techniques can produce a high efficiency however the feature extraction process in this approach is complex and time consuming. Beyond this the usage of character thinners could cause the loss of certain features.

In 2012 an approach to recognize English characters was proposed. It was based on Fuzzy classification theory where a membership function was used. This function was based on the coordinates (x,y) and the length of the character. The degree of similarity between the character and trained image was used to recognize the alphabet. Beyond this there are many other drawbacks in the existing systems such as

- It can take only limited amount of datasets.
- Due to complexness of recognizing cursive alphabets and different handwriting styles, it is implemented only for 20 data entries.
- Works only for individual characters and not cursive styles and uses a less exhaustive greedy search algorithm for decoding.
- Less accurate to classify similar alphabets.
- Does not work in unison with different network methods.
- Does not use neural networks and machine learning concepts and does not use datasets to train models.

B. Proposed System

The proposed system incorporates certain features which enables to eradicate quite a few disadvantages of existing systems. The use of the CNN algorithm in itself increases the efficiency of the recognition system. Furthermore, the use of multiple hidden layers aids in accurate prediction and improved recognition of cursive handwriting. Our proposed system uses an exhaustive but carefully cleaned and calibrated dataset which is vital to obtain high levels of efficiency. The system also provides a comparison between the efficiency of various algorithms when applied to the use case. Thus, the comparative study gives the user an intuition into how powerful is that particular algorithm for the particular application. Thus, the system is a combination of user application and an analytical study.

3. CONVOLUTIONAL NEURAL NEWTWORK ALGORITHM

CNN or convolutional neural network is a class of deep, feed-forward artificial neural networks that has been applied to analyse visual imagery. It uses little pre-processing compared to other image recognition algorithms. It removes unwanted components and features by learning about the data sets that in traditional algorithms were hand engineered. CNN is used in image and video recognition which is very useful in our project. A CNN consists of an input layer and an output layer with multiple hidden layers. The multiple layers consists of convolutional layers, pooling layers, fully connected layers and normalisation.

- Convolutional layer:

  Convolutional layers apply a convolution operation to the input, passing the result to the next layer. The convolution emulates the response of an individual neuron to visual stimuli. Each convolutional neuron processes data only for its receptive field.

- Pooling layer:

  Convolutional networks may include local or global pooling, which combine the outputs of neuron clusters at one layer into a single neuron in the next layer.

- Fully connected layer:

  Fully connected layers connect every neuron in one layer to every neuron in another layer. It is in principle the same as the traditional multi-layer perceptron neural network.

- Weights:

  CNNs share weights in convolutional layers, which means that the same filter (weights bank) used for each receptive in the layer; this reduces memory footprint and improves performance.

  Convolutional neural networks are biologically inspired variants of multilayer perceptron's, designed to emulate the behaviour of a visual cortex. CNNs have many distinguishing features.

3D volumes of neurons: The layers of a CNN have neurons arranged in 3 dimensions: width, height and depth. The neurons inside a layer are connected to only a small region of the layer before it, called a receptive field. Distinct types of layers, both locally and completely connected, are stacked to form a CNN architecture

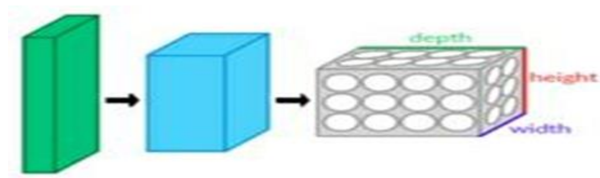

Fig.2.Spatial arrangement of image in CNN

Local connectivity: following the concept of receptive fields, CNNs exploit spatial locality by enforcing a local connectivity pattern between neurons of adjacent layers. The architecture thus ensures that the learnt "filters" produce the strongest response to a spatially local input pattern.

Shared weights: In CNNs, each filter is replicated across the entire visual field. These replicated units share the same parameterization (weight vector and bias) and form a feature map. This means that all the neurons in a given convolutional layer respond to the same feature within their specific response field.

Together, these properties allow CNNs to achieve better generalization on vision problems. Weight sharing dramatically reduces the number of free parameters learned, thus lowering the memory requirements for running the network and allowing the training of larger, more powerful networks. CNN offers much more efficiency in image processing than other algorithms.

4. MATHEMATICAL MODELING

In our proposed system we are using sigmoid function for the prediction of the handwritten letters.

The sigmoid function is given as:

H(X)=1/(1+e^(-W.X)) (1)

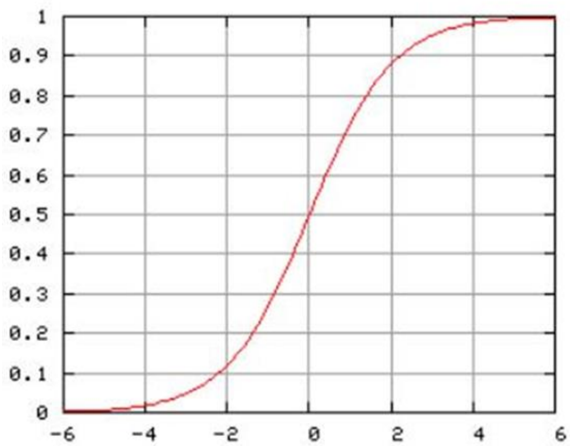

Fig.3.The sigmoid function

The value of h(x) will lie between 0 and 1 as lower bound of sigmoid function is 0 and upper bound is 1.

The above symbols are represented as:

H(x)=predicted value

W=weights of the layers

X=features of the model

The above function seems to be very straight forward but it’s getting complicated when hidden layer’s role come into play. We are using the multiple hidden layers in our proposed system in order to increase the efficiency of the model. The intuition of our model is given as:

Data in the input layer is labeled as x with subscripts 1, 2, 3, …, m. Neurons in the hidden layer are labeled as h with subscripts 1, 2, 3, …, n. Note for hidden layer it’s n and not m, since the number of hidden layer neurons might differ from the number in input data. And as you see in the graph below, the hidden layer neurons are also labeled with superscript 1. This is so that when you have several hidden layers, you can identify which hidden layer it is: first hidden layer has superscript 1, second hidden layer has superscript 2, and so on.

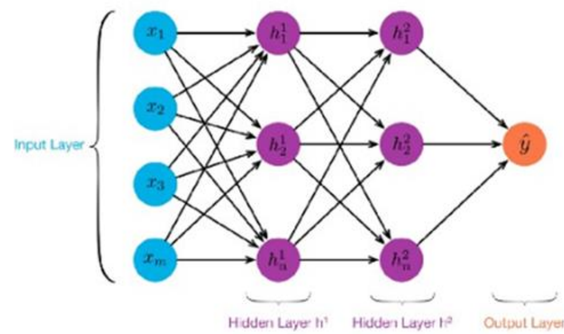

Fig.4.The neural network model

The takeaways of the model is given as:

- With m features in input x, you need m weights to perform dot product.
- With n hidden neurons in the hidden layer, you need n sets of weights(w1,w2,….wn) for performing a dot product.
- With 1 hidden layering dot products can be performed to get the hidden output h(h1,h2….).
- Then it’s just like the single layer perceptron, we use hidden outputs h(h1,h2,…) as input data that has n features, perform dot product with 1 set of n weights(w1,w2,w3,…wn) to get our final output y.

W.X=w1x1+w2x2+….+wmxm=Σ wixi *(2)*

Finally, insert the values of dot product into the sigmoid function to get the values of the outputs.

Efficiency is one of the main objective of our model and in order to achieve that aim we use vector method approach instead of loops. Vector method approach give as better efficiency as computation is faster in vector method.

5. IMPLEMENTATION

The project is implemented in five modules: Dataset collection which involves obtaining sample handwritings, designing of an apt user interface for interactivity, the training of the neural network one important step in this process is segmentation where individual characters are identified and segmented out of the handwritten text, graphical and algorithmic analysis and finally extraction of text into a text file.

The MATLAB Neural Network Toolbox provides numerous libraries facilitating the implementation of above modules. MATLAB also has useful libraries for graphical user interface design. Thus, the complete implementation is done on MATLAB.

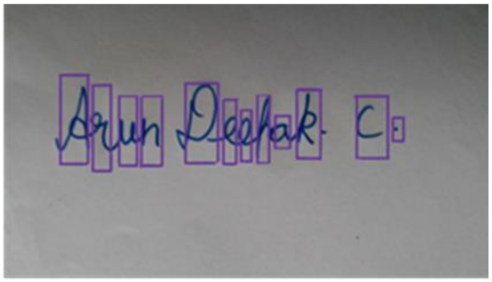

Fig.5.Segmentation of characters

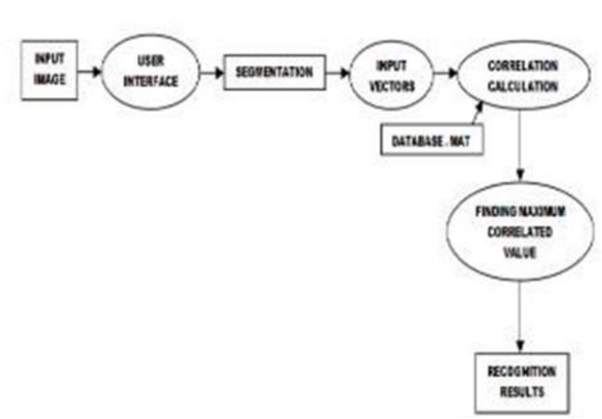

Fig.6.Modules

6. COMPARATIVE STUDY OF ALGORITHMS

The comparison of about nine different algorithms have been performed on the handwriting recognition system and the results obtained suggests that the CNN algorithm which the system has used is the most efficient with 95% recognition rate. Table 1 shows the comparison of algorithms used in the existing systems versus the CNN algorithm this system used. It gives conclusive evidence of improvement in recognition rate from existing systems.

Table 1. Recognition rates of various algorithms

Segmentation method	**Recognition rate**	**Comments**
Artificial neural networks	75%	100,000 training pattern used.
Feature Extraction	75.98%	Synthetically generated handwritten data is used
Heuristic algorithm	85%	Only 50 mail envelopes are taken
Feature Extraction	88%	Robust hybrid feature extraction is used
Reading by features	88.5%	The alphabets are classified using Bouma's shape.
Hough Transform	90%	A database of 2014 binary images is used.
Otsu Algorithm	91%	Neuro rule based segmentation algorithm is used.
Multilayer perceptron	91%	Feed forward based artificial neural network that uses non-linear activation function.
Convolutional neural networks	95%	variation of multilayer perceptrons designed to require minimal preprocessing.

7. CONCLUSION

The above system efficiently converts handwritten text into a text file using neural networks thereby automating the digital conversion process vital to many real-world applications. It also provides a lucid comparative study on various algorithms and the graphs reflect the efficiency of the CNN algorithm to be the highest among the ones studied. The use of an exhaustive data set to train the neural network has further improved the reliability of character recognition over the previous systems. In spite of employing powerful algorithms the recognition of cursive handwriting is rather an arduous task which requires more research before it is deployed in a large scale.

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