



# Application of Artificial Neural Network Techniques in Text Recognition from an Image

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**ABSTRACT:** In this paper, a model is proposed that works on the concept of recognizing text from an image with the help of neural network. Firstly, the text is extracted from the input image. This is one of the most important tasks of this system. Then this extracted text goes through various pre-processing steps that include binarization, normalization, converting text on gray scale, point detection, edge detection, angular rotation etc. After the pre-processing the text is segmented into various sub sections for better functioning of the system and to maintain the accuracy. Important features of the segmented text are extracted in the process of feature extraction. These features helps to differentiate the characters or segments from one another. Finally, the text is classified and is fed to the neural network for the training purpose. Therefore, neural network learns in an unsupervised manner. In the testing phase, the neural network based on the trained data gives the result as recognized text. In this way, the system works in 2 phases i.e. training phase and testing phase and attains state-of-the-art performance.

**KEYWORDS:** text recognition system; text extraction; text recognition; feature extraction; unsupervised learning;neural network.

## I. INTRODUCTION

Text recognition system that can recognize text from natural images finds its application in many fields. For example, this system can be helpful for visually disabled user to find information in different environments as in grocery stores [1]. This system can also be applied to a self-dependent navigation system to provide additional information. Generally, by text recognition in a natural image we can get extra information about the image or scene. However, text recognition in natural images has its own level of difficulties. While previous methods achieved high performance on optical character recognition (OCR) for scanned documents, the problem of recognizing text in natural images is not so far solved. Scene text recognition is much more challenging due to the variations in backgrounds, textures, fonts, and lighting conditions that are present in such images. Therefore, preparing a text recognition system requires models and representations that are not affected by these variations. In some systems, models such as conditional random fields (CRFs) [2] or pictorial-structure models [38] are necessary to integrate the detected or recognized responses into a complete system. In this paper, an alternative approach of text recognition based upon recent advances and unsupervised feature vector learning is proposed. The algorithms are designed to learn the representations from the data by themselves and thus present an alternative approach for the features used for representation. Such algorithms have already successful in many fields, such as visual recognition [4] and action classification [5]. Here in case of text recognition, the system has achieved highly efficient results in text detection and character recognition using a simple feature-extraction architecture and synthetic data. By the use of these feature-extracting algorithms, we were able to make a set of features that are used particularly for the text recognition problem and to train the neural network. These learning features were then combined into a larger and trained convolutional neural network (CNN). CNNs are neural networks that works in a hierarchical fashion and have huge capacity of representation and have been very successfully applied to many problems such as handwriting recognition [6], visual object recognition [7], and character recognition [9]. By using these architectures, training of highly efficient neural network for text extraction and character recognition is done. Although there are many differences between the two tasks i.e. text detection and character recognition, the system have used structurally similar architectures for both the text detection and character recognition. Consequently, due to the increased accuracy and robustness of these models, this text recognition system is constructed successfully and efficiently. However, the system achieved high performance on the standard benchmarks. The results



# International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

thus shows the flexibility of the construction of a complete recognition system that does not depend on hand-engineered features or some prior knowledge. Text Recognition handles the problem of recognizing optically scanned text. Text recognition can be done off-line when the writing of the text is completed, whereas in on-line recognition the system recognizes the text as soon as they are drawn. The system can recognize both, that is, the handwritten as well as the printed documents but the performance of the system is highly dependent on the amount of input given to the system [12]. If the input text is more constrained, the performance of the system will increase. But if the input text is fully unconstrained, the system performance is not too bad [11]. As we all know that the computer is faster and more technically advanced than humans, therefore, this system will bring the performance of computer to an ideal state. Since, in this changing scenario the technology should also get some more advanced.

## II. RELATED WORK

### A. Scene Text Recognition :

Text recognition is a delinquent in machine learning and computer visualization that dates back some years. At the high level, the common problem of text recognition consists of two main components: text detection and text recognition. First, in text detection, the goal is to locate different words or lines of text. Then, once the areas of text are located in the image, the real words and lines of text in those areas are found out. Over the years, so much time and exertion have been devoted in resolving different modules of the text recognition problem. As a straight result, algorithms exist that attain enormously high performance on dedicated tasks such as digit recognition in unnatural settings. For example, the system in [21] is able to attain near human performance on handwritten digit recognition. Similarly, the system in [22] attains very high precision on the task of recognizing English characters. Despite these advances in the field of text recognition, however, the more general task of detecting and recognizing text in complex scenes still remains an exposed problem. Much of the fiction on scene text recognition tends to focus on a sub-component of the text recognition system. The three main sub systems that have established much of this attention are text detection, word segmentation, and word recognition. Below each of these subsystems are described individually.

1. Text Extraction: As mentioned above, the objective of text detection or localization is to find candidate areas of text in a given input image. Normally, the detection task resembles to recognizing a bounding box or rectangle for each word or for each line of text in the image. Many alternative methods have been proposed for text detection. These methods have variety from using simple off-the-shelf classifiers with hand-coded features [23] to much more refined multi-stage pipelines integrating many different algorithms and processing layers [24, 2]. One example of an elaborate multi-stage pipeline is the system proposed by [2], which employs extensive pre-processing stages such as binarization of the input image, followed by connected component analysis through a conditional random field (CRF) to identify lines of text. Still others in the field of text detection have established clever hand engineered features and conversions well suited for the task at hand. For example, the system in [25] exploits the uniformity of stroke width in characters to develop a robust, state-of-the-art text detection system.

2. Text Segmentation and Recognition: The story is alike in the case of text segmentation and recognition. In the case of segmentation, the task is to take a single word or single line of text and produce individual characters or individual words. In the situation of a recognition system, this input line or word would relate to a region of text identified by the text detection system. It follows that if each character in the word is recognized, the characters together to identify the fundamental word can be concatenated. Thus, the final result of the segmentation and recognition stages is a set of interpreted bounding boxes. As in the case of detection, a widespread variety of techniques has been applied to the problem of segmentation and recognition. These techniques include various senses of probabilistic graphical models for joint segmentation and recognition [26, 27, 28], a multi-stage postulate verification pipeline [29] that influences geometric models, language models, and other forms of prior knowledge in a complete recognition system, as well as a pictographic structure model [3] that combines a simple character classifier along with geometric constraints on character locations that also achieves recognition. Because of the environment of the recognition problem, many of these systems include indefinite degrees of prior knowledge in the form of regular models or language models. Geometric typographic models, like the one used in [29], encrypt knowledge such as the fact that the height of certain characters is larger than that of others (e.g., the letter 'b' against the letter 'c') or that certain characters are transposable because they have similar appearances (e.g., uppercase 'S' and lowercase 's'). Similarly, language models provide information about how characters are naturally distributed within words. For

# International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

example, a language model might encode the fact that certain bigrams, or sequences of two characters, occur more frequently than others in the English language.

## B. Feed Forward Network:

Consider a supervised learning scenario where we are given a set of labeled data  $\{x^{(i)}, y^{(i)}\}$ . Here,  $x^{(i)}$  and  $y^{(i)}$  denote the features and label, respectively of the  $i^{\text{th}}$  training example. At a elevated then, neural networks deliver a way of representing a composite, non-linear function  $h_W(x)$  of our input variable  $x$ . The function  $h_W(x)$  is parameterized by a weights matrix  $W$  that we can tune to fit our data. Figure 1 shows a simple neural network consisting of three input units or neurons, denoted  $x_{11}$ ,  $x_{12}$ , and  $x_{13}$ , and one output unit  $y = h_W(x_{11}, x_{12}, x_{13})$ .

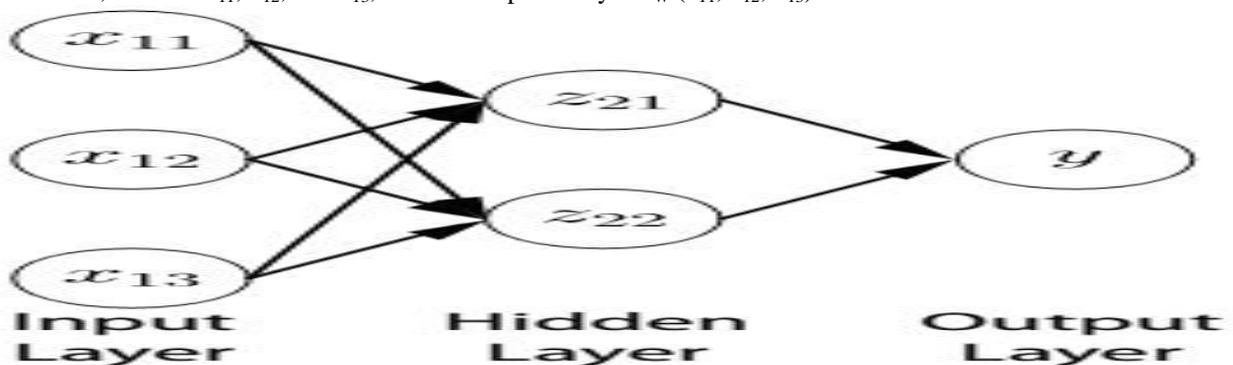


Figure 1: A simple feed-forward neural network.

A neural network is usually organized into multiple coats. For instance, the network in Figure 1 consists of three layers: the input layer, the hidden layer, and the output layer. Aside from the neurons in the input layer, each neuron  $x_i$  in the neural network is a computational component that takes in as input the ethics of the neurons from the earlier layer that feed into  $x_i$ . As a tangible example, the inputs to the neuron branded  $z_{21}$  in the sample neural network is  $x_{11}$ ,  $x_{12}$ , and  $x_{13}$  and the input to  $y$  is  $z_{21}$  and  $z_{22}$ . Given its inputs, a neuron first computes a weighted linear combination of those inputs. More precisely, let  $x_1, \dots, x_n$  denote the inputs to a neuron  $z_j$ . Then, we first compute

$$a_j = \sum_{i=1}^n w_{ji}x_i + b_j$$

where  $w_{ji}$  is a parameter describing the interface between  $z_j$  and the input neuron  $x_i$ . The  $b_j$  term is a prejudice or intercept term related with neuron  $z_j$ . Then apply a nonlinear start function [39] to  $a_j$ . Some common start functions include the sigmoid and the hyperbolic tangent purposes. In specific, the activation or value of the neuron  $z_j$  is defined to be

$$z_j = h(a_j) = h\left(\sum_{i=1}^n w_{ji}x_i + b_j\right)$$

where  $h$  in this case is our nonlinear start purpose. Given a set of input variables  $x$ , and weights  $W$  (one term for all edge and a bias term for all node without the ones in the input layer), calculate the activation of each neuron by next the above steps. Since the start of each neuron depends only upon the standards of neurons in previous layers, we compute the starts starting from the first unseen layer (which depend only upon the input values) and continue layer-wise through the network. This procedure where info spreads through the network is called the forward-propagation step. At the end of the forward-propagation step, we obtain a set of outputs  $y = h_W(x)$ . In the case where we are execution binary classification, we can opinion the output  $y$  as a classification consequence for the input  $x$ . The limits  $W$  in the neural network are included of the weight relations for each of the limits as well as a partiality term for each of the nodes, without the ones in the input layer. Given our categorized training set  $\{(x^i, y^i)\}$ , the impartial is to learn the parameters  $W$  so as to minimize certain objective or loss function. In the case anywhere we are execution binary classification, a simple objective purpose might the classification fault over the entire dataset (e.g., the mean squared

# International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

difference between the predicted label  $\hat{y} = h_w(x)$  and the true label  $y$ ). The normal approach to learning the parameters  $W$  in order to minimize the desired objective is the fault back-propagation algorithm [37].

### III. PROPOSED WORK

In this framework the word recognition task is done comprehensively on the whole image and it does not require and labelled data as in other character recognition techniques. The framework is implemented with the help of artificial neural network which is being trained on synthetic data. Synthetic data is of a kind that replaces original data in the most realistic data and gives huge amount of training data which uncovers more chances for recognition systems. This system deals with three major tasks:

- Extraction of text from a scene.
- Performing word recognition on whole image as an extension of character recognition system.
- Make use of synthetic data to train the network for the recognition process.

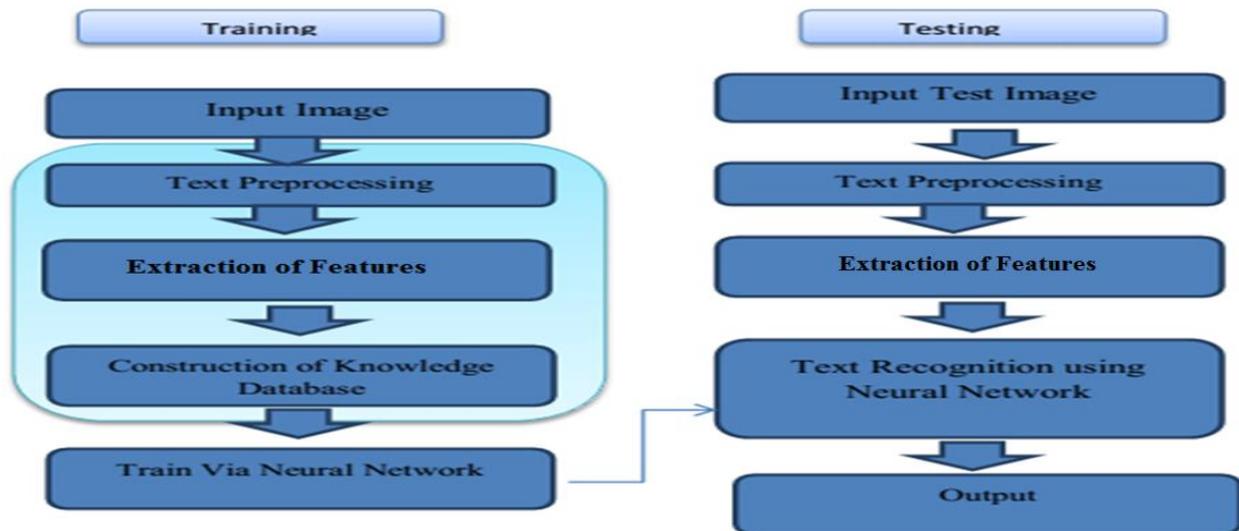


Figure 2: Proposed Model

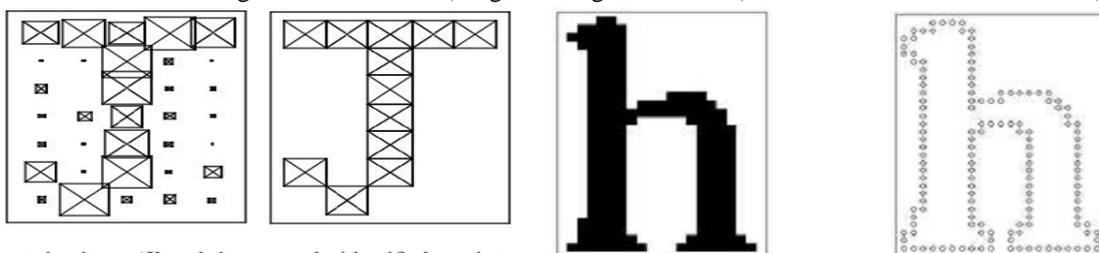
Modules of the System:

#### A. Binarization:

It converts any image into a series of black text written on white background. Effects like contrast, sharpness etc. can also be easily handled once the image has been binarized. If an image has had its background normalized to a constant value, it can be binarized by a global value chosen to be less than the background by an appropriate amount. Important tasks performed in binarization:

- Noise removal:

Noise removal is used to enhance the image. It is used to remove any type of unwanted bit-patterns that may affect the output. Various filtering operations can be applied to remove noise e.g. Median Filter, Weiner filter etc. Here we have used median filter. Filtered Image = Median Filter (Original Image, Filter Size). Here we have taken filter size (5, 5).



The noisy input 'J' and the correctly identified version

Figure 3: Illustrates Noise Removal from character image. Figure 4: Illustrates Edge Detection process.



# International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

- **Edge Detection:**

The Edge/boundary detection of image is done for easier detection and extraction of applicable features of the image as shown in figure 4. After finding the edges the image, it undergoes the process of dilation. In this process, the holes present in the image are filled. These operations performed on the input image makes the image suitable for segmentation [15].

- **Smoothing:**

Objective of smoothing is to smooth the edges and the shape of broken/distorted images. In this process, some bits can be added/removes from the input text in order to attain accuracy.

*B. Segmentation:*

It is integral part of text recognition system. Segmentation assures efficiency of classification and recognition. Accuracy of character recognition heavily depends upon segmentation phase. Incorrect segmentation leads to incorrect recognition. Segmentation phase include line segmentation, character and word segmentation. It is important to obtain complete segmented character without any noise to ensure quality feature extraction. Firstly in this process, each line of the text image is segmented and then each character is separated from the segmented lines. If the text is mixed with some images then we require a candidate block to segment text from the image.

*C. Feature Extraction:*

The main aim of feature extraction is to make improvement in the accuracy and speed of the classifier for the pattern recognition. The extraction of the features of the characters is done in such a way that the complete portion of binary image covered and there is a distinct property associated with the each position. So we can say that feature extraction is a precise way in which a pattern can be described. It is one of the most important parts of this system [42].

Method used for feature extraction:

Here the method used is zoning. Zoning is one of the feature most popular and simple to implement feature extraction method. An  $(n*m)$  grid is superimposed on the character image and then for each zone average value is computed giving a feature vector of length  $(n*m)$ , if required further we can compute the average on this zone again in row wise and column wise respectively.

Algorithm for feature extraction using zoning method (as in [43]):

Input: Preprocessed numeral image

Output: Features for Classification and Recognition

Method Begins

Step 1: Compute the input image centroid

Step 2: Divide the input image into  $n$  equal zones.

Step 3: Compute the distance between the image centroid to each pixel present in the Zone.

Step 4: Repeat step 3 for the entire pixel present in the zone.

Step 5: Compute average distance between these points.

Step 6: Compute the zone centroid

Step 7: Compute the distance between the zone centroid to each pixel present in the Zone.

Step 8: Repeat step 7 for the entire pixel present in the zone.

Step 9: Compute average distance between these points.

Step 10: Repeat the steps 3-9 sequentially for the entire zone.

Step 11: Finally,  $2*n$  such features will be obtained for classification and recognition.

Method Ends

*D. Recognition:*

Here in this section neural network is used for the classification of extracted feature vector into their respective classes. Since character recognition is one of the best applications of neural network, therefore, neural network is used as an

# International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

important tool in this system. A multilayer feed-forward back-propagation network is created and is trained on synthetic data in the training phase. For testing phase, multilayer perceptron network is implemented.

### Dataset Used:

Dataset used for training and recognition is same. Here street view text images and some images of natural scene with text as well are used. Images are all in jpeg format.



Figure 5: Some images from the dataset

## IV. RESULTS

A text recognition system that work in two phases, that is, text detection and text recognition is prepared. Text detector extracts text from the input image and apply various noise removal, smoothing, skewness removal, binarization edge detection, segmentation and feature extraction methods on the extracted text. These feature vectors are used as dataset for classification of the vectors into their respected classes. After this the network is trained and hence when an input image is given to the network it recognizes text using the various recognition algorithms and gives recognized text as output.

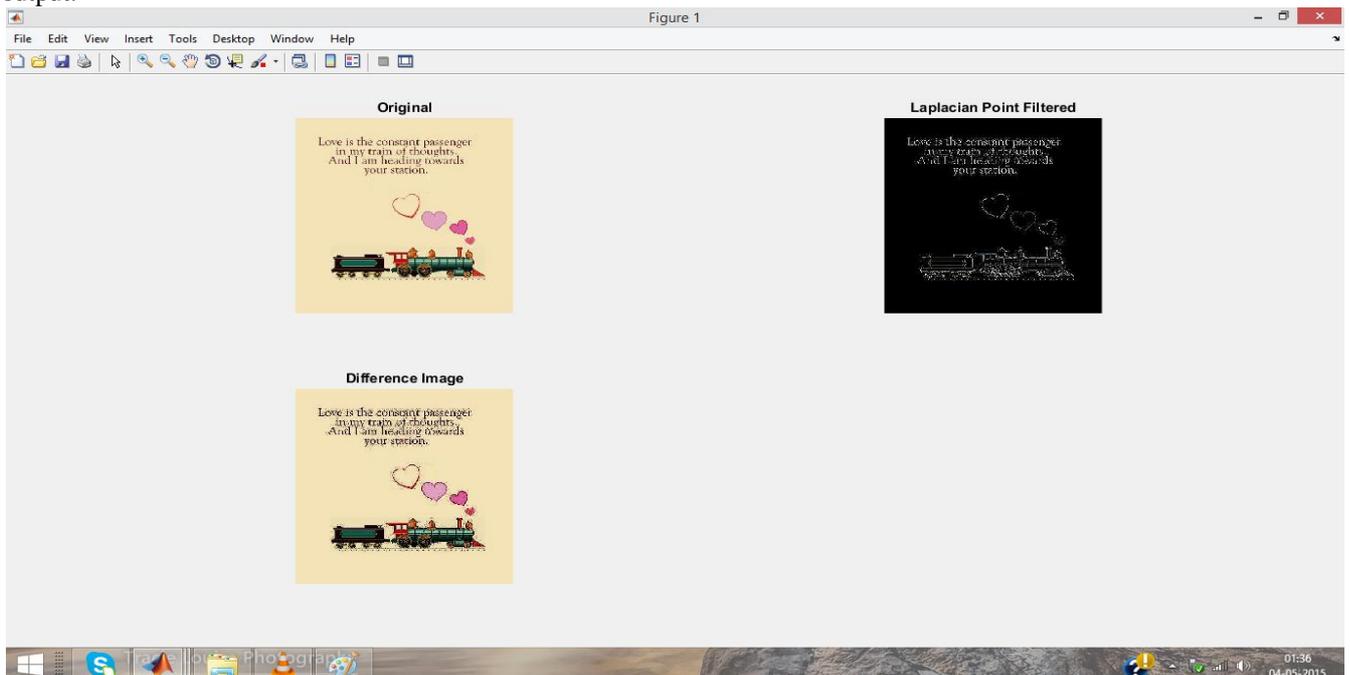


Figure 6: Original input image with the result after performing point detection.

# International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

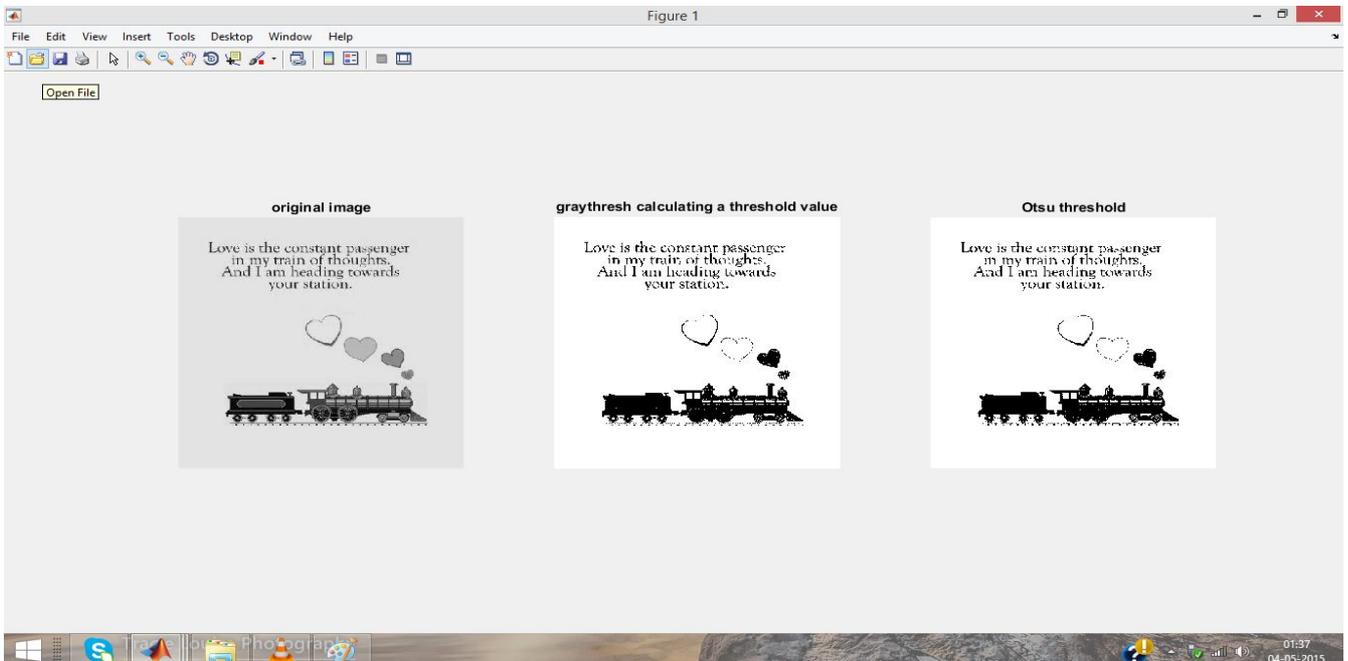


Figure 7: Result after performing segmentation. Since the text and image are mixed, therefore, we need candidate box for segmentation. This will help to extract text from the input image.

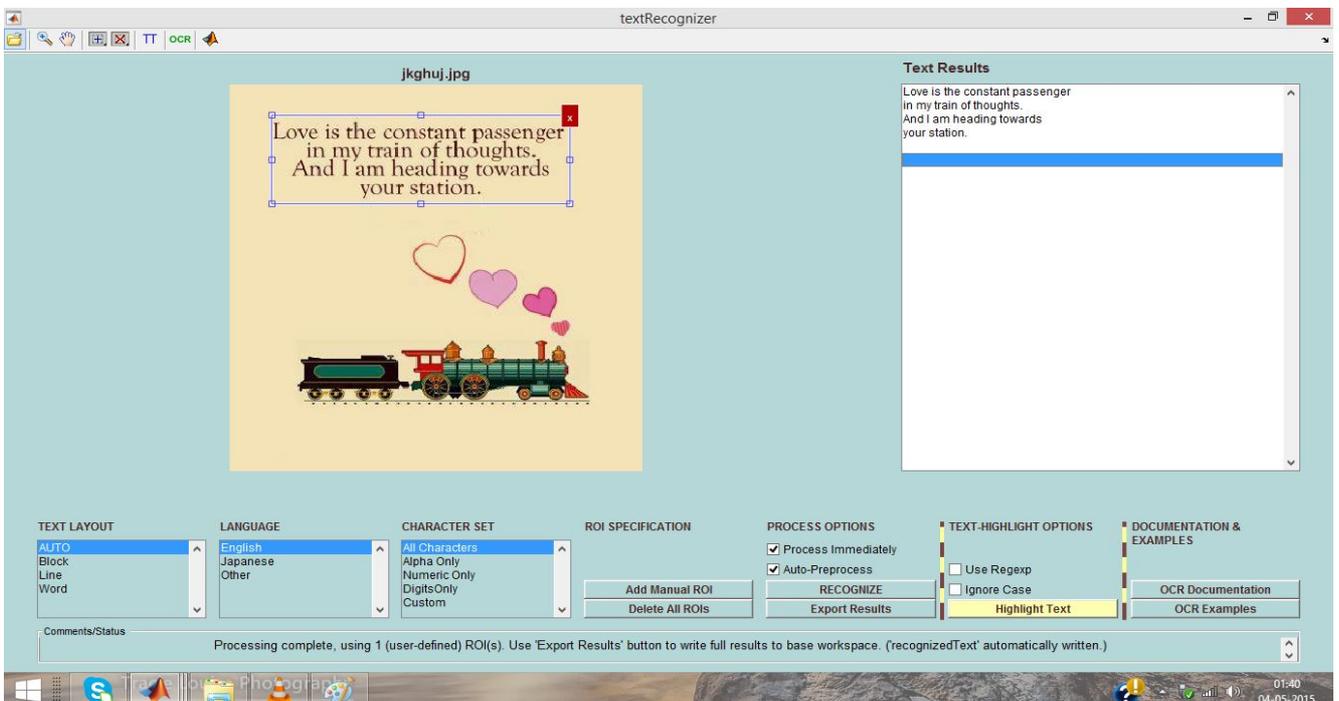


Figure 8: Final result showing the candidate block and the recognized text.



# International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

## V. CONCLUSION AND FUTURE WORK

The model described in this paper presents an alternative approach for solving the problem of text recognition using artificial neural network techniques with the help of unsupervised learning methodology. For training, the same architecture as for recognition is used to attain high accuracy and robustness of the text detection and text recognition modules and thus the system has become different from the previous such systems. As the evidence of the high performance of the system, the state-of-the-art results of text recognition in images with text are shown. Hence, the system have shown state-of-the-art performance after being compared to various standard benchmarks. Few limitations of the text recognition system are also highlighted and future work is proposed. First limitation is the gap between the performances of the proposed system in different types of recognition tasks because the frame that bounds/extracts text from the image for text detection were not perfectly cropped. Hence, this decreases the performance of the text recognition system because of the poorer quality of the cropped text provided by the text detector. Second limitation is the fact that the text recognition system is highly dependent on text detection system. Thus, the system needs to be improved so that it might become less dependent on the text detector and become autonomous. Third limitation of the text recognition system was that the detection system is aimed on finding only horizontal lines of text in the image. This restriction became particularly challenging in cases where the text was slightly skewed, and thus acted to extent upon multiple lines. In these cases, the text detector did not to provide a perfectly-cropped bounding box for the whole word or line. Thus, providing a direction to the recognition system so that it is able to perform in cases where the text is vertically aligned. These limitations give direction for future work.

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(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

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