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Detection and Recognition of Text Based On OCR and CNN

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ABSTRACT

Optical character recognitions or optical character readers is the conversion of electronic or mechanical image of typed, handwritten or printed text into machine-encoded text, whether from a scanned document, a photo of a documents or image. An image Character Recognition is essential for transmission and storage of digital images. Many research works have been developed for lossless image compression and decompression. However, higher quality lossless image compression was not achieved. In this paper DCT Feature Extraction and Huffman Encode and Decode from Images (DCT-HED) data security system for Feature Extraction and Encode and Decode Process and Text Recognition Classification. The main objective of this work is to evaluate the Optical Character Recognitions (OCR) is to classify optical patterns (often contained in a digital image) corresponding to alphanumeric or other characters. The process of OCR involves several steps including Pre-Processing, feature extraction, and classification. The Coefficient-based Discrete Cosine Transform initially partitions the image into coefficients to decide upon which coefficient value to be considered for encoding. Character recognition is significant for transmission and storage of digital images. During the transmission, storage of raw images requires vast amount of memory space. Therefore, there is a necessity for reducing the size of image before sending or storing. Extensive experiments carried out on the Text images have revealed the outstanding performance of the proposed CDCT (Coefficient Discrete cosine transform) model when benchmarked with various well established state-of-the-art schemes. The results obtained by CDCT witness a significant increase in compression ratio by reducing the total error while compressing with minimized computational complexity when compared with the results produced by the other state-of-the art methods considered.

Keywords: OCR (Optical character recognition), DCT (Discrete Cosine Transform), Feature Extraction, Classification, Error rate, Computational Complexity.

I. INTRODUCTION

Optical Character recognition extracted from in multimedia, communications, surveillance and security, medical imaging, Documents and many more. Transmission of Data use of the internet and mobile devices facilitates the creation, transmission and sharing of digital images. Image security based on creates a critical need for effective image protection techniques. Optical character recognition is significant in digital image processing for transmission. An image Encode and Decode is the process of minimizing irrelevance and redundancy of image data for storing or transmitting data in an effective manner. The image compression is classified into type's namely lossless image compression and lossless image compression. In lossless image compression, the original image is efficiently recovered from the compressed image. The transformation model based on Open Computing Language and Discrete Cosine Transform merging the DCT and quantization showed a memory map mechanism reducing the CPU overhead and improving the compression performance. In Innovative Lossless Compression method for Discrete Color Images, has the main idea of constructing fixed-to-variable codebook is that instead of using row-column values in images, it involves mathematical computations that removes redundancy. It is critical to find which kind of local image features are required for a particular application, how to extract them, and how to apply them in the design of image processing. The Paper work presented in this thesis is in the topic domain of image feature extraction and Classification Process.

II. RELATED WORKS

Zuo et al. proposed an Encoder-Decoder framework for scene text recognition which combines connection time classification (CTC) and attention mechanism that converts the natural text into a sequence mark. The feature extraction of input image is carried out by CNN and extracted features are encoded using Bidirectional Long Short Term Memory (BiLSTM) and generate the feature maps. CTC and attention mechanism is used in the decoder layer to decode into the output. The text recognition model includes three parts: feature extraction, sequence analysis, and CTC-Attention joint mechanism decoding. The performance of the proposed system is evaluated using four datasets: SVT (Street View Text), IIIT5K Words, ICDAR2003 and ICDAR2013. The system gets more accuracy by using the dataset ICDAR2013.

Chernyshova et al. proposed Two-step CNN framework for text line recognition. The method is for the ID recognition of camera captured images. Text line recognition is the part of the field recognition step in the ID recognition. The two ANNs are used Gao et al. proposed a detection and verification model based on Single Shot Multibox Detector (SSD) and Encode Decoder network which consist of initial text detection with text localization neural network and eliminating background regions with text verification model. The text localization neural network is based on SSD which detect only horizontal text. The text verification model is mainly based on Encoder Decoder framework which deletes the non-text areas detects from initial detection. The BiGRU (Bidirectional Gated Recurrent Unit) network in the encoder layer encodes context information with text image features. The GRU (Gated Recurrent Unit) network with attention mechanism in decoder layer that decodes feature sequences into words. The performance of the proposed system is evaluated using the dataset: ICDAR 2017. The evaluation metrics used are Precision, Recall and F-Measures.

Liang et al. proposed a RNTR-Net: A Robust Natural Text Recognition Network. RNTR is the combination of Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN). CNN is used for feature extraction and RNN is used for sequence recognition. The method of text recognition includes mainly three steps. Feature extraction, Sequence Recognition and Transcription. The input field image first passed through convolution layer with residual block and generates the feature maps. The feature sequences from feature extraction are passed through two BLSTM's (Bidirectional Long Short Term Memory) and these are very effective for modeling and predicting sequential data. The transcription layer which translates the frame sequences to final output. The performance of the proposed system evaluated using the datasets: ICDAR 2003, ICDAR 2013, SVT and IIT5K. The method has 96.7% accuracy by using the dataset IIIT5K.

Liu et al. proposes scene text detection with Feature Pyramid Based Text Proposal Network (FTPN). The CNN section uses a feature pyramid network to extract the multiscale feature of an image. Bidirectional Long Short Term Memory (Bi-LSTM) is used for encoding. Region of Interest (RO) pooling is used to speed up the training and testing process. Text connector is used in the last stage to construct the final output. The Performance of the proposed system evaluated by using the datasets: ICDAR 2013, ICDAR2015. The evaluation Metrics used are Precision, Recall and F-measure.

Su et al. proposed image processing technologies for text recognition with the combination of Optical Character Recognition (OCR) technologies. The proposed method includes a character recognition system for cosmetic related advertisement images. Also a text detection and recognition system is used for natural scenes. The first system converts the input image into a gray scale image and simplifies the image, and then searches for counters using the sobel filter. The next step is the binarization process. This process detects the limit value of the gray scale image and checks whether a pixel has a specific value or not. Dilation adds pixels to the object boundaries and erosion removes pixels on object boundaries. In next step redilation is performed and seeks the character contours and then Region of Interest (ROI) is lassoed. The last operation is character recognition which identifies the individual characters in an image. The performance of the system is evaluated by using the dataset ICDAR Robust Reading Competition used as test images. The evaluation metrics used are Accuracy, Recall and F1- measures. The system achieved 93% accuracy.

Ghoshal and Banerjee proposed an improved scene text and document image binarization scheme. This method is more effective than other binarization methods for the natural image, which contains lower resolution, noise, lower visual acuity, and unbalanced light. This is a new approach to natural scene text image binarization by tracking the text border based on edge and gray level variant information. In addition, the broken boundaries are connected to form a complete boundary map. An adaptive threshold is set here based on the boundary edge information for effective binarization of the image. The proposed method first read the image and computes the variance matrix. To obtain binarized image different adaptive thresholding techniques are applied. Experiments are conducted on the datasets of ICDAR 2003 Robust Reading Competition, ICDAR 2011 Born Digital Dataset, Street View Text (SVT) Dataset, DIBCO dataset and laboratory made Bangla Dataset. The performance of the system is evaluated by using Precision, Recall and F- measures.

Rampurkar et al. proposed text detection from complex images using morphological techniques like erosion and dilation. There is a color based partition is performed on the input image having text. Next step is the connected component labeling which is used to detect the connected regions in color and digital images. In the adjacent character grouping method, the sibling groups of each character candidate are treated as string segments and then the fragmented sibling groups are merged into the text. Text line grouping methods is used to locate text strings with arbitrary orientations. The evaluation metrics used are Precision and Recall.

Chidiac et al. proposed a robust algorithm for text extraction from images. Here Maximally Stable Extremal Regions (MSER) method is used instead of performing simple thresholding method. It is a type of blob detection in images and extracting a comprehensive number of corresponding image elements contributes to wide baseline matching. The MSER enhancer is enhances the detected region. Stroke Width Transform (SWT) is a technique used to extract text from noisy natural scene image, by isolating shapes it shares a constant stroke width and produced more reliable results. The resulting system is to detect text regardless of its scale, font and direction. Then filtering is applied on it which is technique that modify or enhancing an image. After filtering the text line is formed with similar height, constant spacing and similar stroke width by grouping connected component. The performance of the proposed system evaluated by using the datasets: ICDAR and KAIST Scene Text database. The evaluation metrics used are Precision Rate, Recall Rate and F-measure.

Ling et al. proposed a model for automatic recognition of vertical texts in natural scene images. The method includes mainly two processes Text localization and segmentation then the second process is Text Recognition. Gray scaling operation is performed on input scene image containing vertical text then a gray scaled scene image containing vertical text is formed. By using MSER Detector gray scaled image with possible candidate characters are formed then the binarization process applied and the output is binary image with possible candidate characters. After dilation binary image with possible candidate characters' regions are formed. The last step is connected component segmentation which eliminates false positives. Segmented text regions obtained from text localization and segmentation in binary image undergoes correction and orientation determination and Optical Character Recognition (OCR). In orientation determination there are three types of vertical texts, Horizontal- stacked, Top-to-Bottom and Bottom-to-Top. Before OCR recognition Top-to-Bottom and Bottom-to-Top vertical texts are rotate 90 degrees. The output of OCR process is a vertical text, then string formation operation is performed on it and the final output is a character string. The performance of the proposed system is evaluated by using the datasets: SVT, MSRA-TD 500.

The evaluation metrics used are Precision, Recall and F- measures.

III. PROPOSED SYSTEM DESIGN

We proposed a model called, Data Folding and Coefficient-based Discrete Cosine Transform (DF-CDCT) for lossless image Encode and Decode which improves the compression ratio and reduces the computational complexity involved during transformation. The Coefficient-based Discrete Cosine Transform initially partitions the image into coefficients to decide upon which coefficient value to be considered for encoding. Next, Probability-based Data Folding for lossless image compression for continuous images follows Probability-based encoding to reduce the computational complexity involved during transformation. In this proposed work the Coefficient-based Discrete Cosine Transform are applied to the images based on the threshold value with mean square. With the transformed images obtained as output, the Probability-based Data Folding for lossless image compression for continuous images is applied aiming at reducing the computational complexity involved during transformation. The experimental results produced are used to find out the best performance among the existing and proposed lossless image compression models. Based on the aforementioned methods and techniques in this paper, Data Folding and Coefficient-based Discrete Cosine Transform (DF-CDCT) for lossless image compression is introduced that not only improves the compression ratio but also reduces the computational complexity involved during transformation of images.

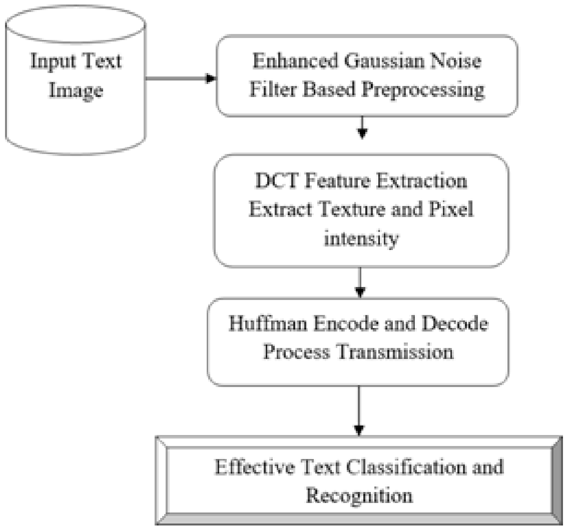


Fig 3.2 Architecture of (DCT-HED) from Images with Optical Character Recognition Method

DCT-HED HAS BEEN CONCERNED IN OUR PROPOSED ALGORITHM

Texture-based representation This feature is exploited for finding the region or object of interest. It is a dimension of intensity difference of a surface applied for computing the characteristics namely smoothness and regularity. Texture necessitates a processing method for producing the descriptors. Texture based system calculates the continuation of gradient configuration in limited parts of an image and then estimates the data on a condensed grid. Then, overlapping narrow disparity standardization was employed to increase the accuracy. In other words, texture feature is applied to evaluate the intensity disparity of surfaces and concerned with object pattern expression. texture features were employed by the feature space to attain efficient object localization.

Texture features for achieving the detected moving regions. With the consideration of texture features, the effectiveness of moving object image segmentation is estimated in a significant manner.

The texture features i.e. correlation and intensity contrast are evaluated by considering the pixel in hyper spectral aerial image. In (DCT-HED) Technique, intensity contrast is determined as the dissimilarity between the pixel and their adjacent pixels in the set of pixels using below mathematical expression,

$I_\varepsilon=\sum_i \sum_j |p_i-p_j|^2$ -> (1)

From above equation (4), 'I_ε'signifies a contrast of image and'p_i' refers a pixel and 'p_j'represents a neighbouring pixel. Then, the correlations between the pixels are measured with help of mean and standard deviation. From that, the correlations between pixels

$corr=\sum_i \sum_j (p_i-\delta)(p_j-\delta)/v^2$ -> (2)

From equation (5), 'corr'represents a correlation between the pixel 'p_i' and its nearest pixels 'p_j'whereas nis a mean and 'v' point outs the deviation. After that, colour features are identified from an input hyper spectral aerial image through changing the RGB image into HSV (hue, saturation, value) colour spaces with help of below formulation,

$\omega_f=1/N \, Inten_{pix}$ -> (3)

From equation (6) 'ω_f' refers the colour feature of hyper spectral aerial image and '$Inten_{pix}$' designates pixel intensity and 'N' is a total number of pixels in an image

COEFFICIENT-BASED DISCRETE COSINE TRANSFORM

The discrete cosine transform (DCT) is used to separate the image in to pixel. DCT is used in signal, image processing especially for lossless compression because it has a strong energy compaction. The lossless image compression ratio of the image was good in number. But the outcome of the image was not good. The quality of the image was not good us lossless image compression technique. DCT image compression may compress the image in nxn metric formation. The DCT transforms the image into the pixels. The pixel of image is transformed in to the level of compression process. Then the image is transformed in to quantization process.

The Coefficient-based Discrete Cosine Transform splits or partitions the given input image into coefficients called sub-bands (i.e. each band possessing a spectral data, therefore corresponding to multi spectral data). The resulting coefficients obtained are then compared with a threshold value. The coefficient values lesser than the threshold value are set to zero and neglected for future reference. On the other hand, the value of coefficients greater than the threshold value forms the basis for encoding. The process of Coefficient-based Discrete Cosine Transform is as given below

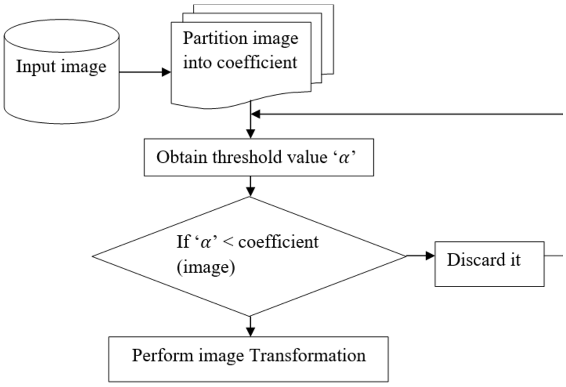


Fig 3.2 Process of Coefficient-based Discrete Cosine Transform

The process of transformation (as in figure 2) for lossless image Encode and Decode is applied to coefficients only from the high pass filter (i.e. neglecting the low coefficient values) with the objective of improving the compression ratio. Subsequently, the results obtained from the coefficients are given to the next level to obtain Three sub-bands ‘L1,L2,L3 ’. This process is repeated up to the desired level of Cosine Transformation computation, resulting in the improved Image Retrieval ratio. Given below shows the algorithm.

// Discreate Cosine Transformation based Image Feature Extraction Algorithm
Input: Text Input Image
Output: Encrypted
Step 1: Begin
Step 2: For each Text Image
Step 3: Apply DCT based Transform for decomposing the image into Three sub bands like L1, L2, L3 with different resolutions using (1) and (2)
Step 4: Perform vector quantization for reducing the number of bits to be transmitted.
Step 5: Perform encoding to reduce the overall size of Text image for transmission
Step 6: End For
Step 7: End

Algorithm 1 Multiscale Approximation DCT Transformation based Image Transformation Algorithm

HUFFMAN ENCODE AND DECODE PROCESS

Huffman Process first creates a tree using the frequencies of the character and then generates code for each character. Data Encode and Decoding is done using the same tree. Huffman Encode and decode process based on Pixel intensity based on neighboring pixel.

This image Encode and Decode algorithm initially takes compressed Text image as input. Then it performs Huffman decoding process for converting of an encoded format back into the original sequence of bits.

given below shows the Probability-based encoding and Decoding.

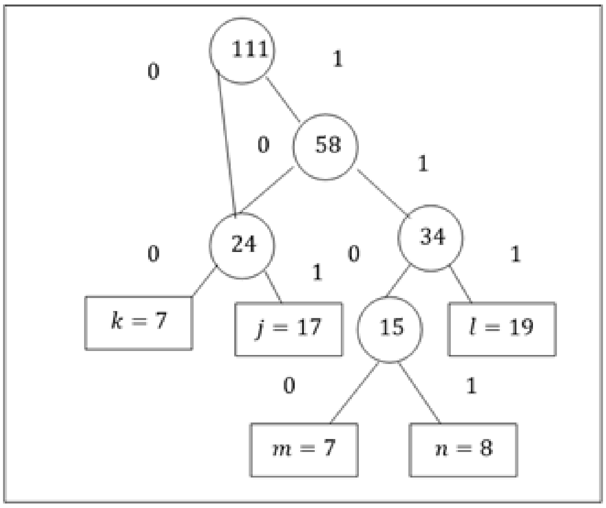


Figure 3 Process of Huffman Encode and Decode

EFFECTIVE TEXT CLASSIFICATION AND RECOGNITION

Classification text recognition defined as sup(〖SI〗

_i⇒ 〖nc〗 _i) denotes the correlation value of 〖SI〗 _i and mean of class ' 〖nc〗 _i', 'j' denotes the number of classes. Depending on the correlation value, classification is determined as,

conf(〖SI〗 _i⇒ 〖nc〗 _i)=((support count of 〖SI〗

_i∪ 〖nc〗 _i)/ 〖SI〗 _i) ->(4)

From (4), conf(〖SI〗 _i⇒ 〖nc〗 _i) denotes the confidence value of how ' 〖SI〗 _i' is related to the mean value 'μ_i' of particular class. After that, classification process is carried out depending on the support and confidence threshold ranges. When classifier categories the Classify image into different classes, threshold ranges are predetermined. The objective of association rule mining is to identify all rules having estimated support and confidence greater than minimum and maximum threshold value. It is given by,

C_j={(θ_min<sup(〖SI〗 _i⇒ 〖mc〗 _i)<θ_max @∅_min<conf(〖SI〗 _i⇒ 〖mc〗 _i)<∅_max) ->(5)

From (5), C_j symbolizes the quadratic associative classifier, θ_min and θ_max represents the minimum and maximum threshold range of the support value. ∅_min and ∅_max are minimum and maximum threshold range of the confidence value. When support value of Classify image and mean within minimum and maximum threshold range of class, then Optimized image is classified into specific class. By this way, quadratic associative classifier classifies the Optimized image into two classes and recognized the user as an authorized user and unauthorized user. By this way, the images are recognized as authorized user and unauthorized one with higher accuracy and lesser time consumption. The algorithmic process of DCT Feature Extraction and Huffman Encode and Decode.

Input: Encrypt $SI1, SI2, SI3, \ldots, SIn$

Output: Increase the recognition accuracy and reduce time consumption

1. Begin
2. Initialize the output classes $Yj = Y1, Y2$
3. Determine mean value nci of classes
4. For each Classified image SIi
5. Calculate the likelihood ratio' L'
6. For each mean value nc_i of classes Calculate support value $sup(SI_i \Rightarrow nc_i)$
7. Measure confidence value $conf(SI_i \Rightarrow nc_i)$
8. If($\theta_{max} < sup(SI_i \Rightarrow nc_i) > \theta_{min}$ && $\emptyset_{max} < conf(SI_i \Rightarrow nc_i) > \emptyset_{min}$) then
9. Classify the Classified image into particular class Y_j
10. End if
11. End for
12. End for
13. End

Algorithm 2: Effective Text Classification and Recognition Algorithm

EXPERIMENTAL SETTINGS

In this research work, the proposed DCT Feature Extraction and Huffman Encode and Decode (DCT-HED) is implemented in MATLAB Software 2015b with Dataset- en-OCR Image Database (https://www.kaggle.com/datasets/thnhhunhtn/dat asetenocr/discussion). Dataset-en-OCR has been released to international community and You work as a social media moderator for your firm. Your key responsibility is to tag uploaded content (images) during Pride Month based on its sentiment (positive, negative, or random) and categorize them for internal reference and Classification Detection.

HARDWARE CONFIGURATION MATLAB

Version: 2015b Version

Processor: Intel (R) Core (TM) i3-4130 CPU @ 3.40GHz

(4th generation)

RAM: 4 GB RAM, DDR3 799MHz

System Type: Windows 10, 64 Bit Operating System Mother Board: ASROCK-H81m-VG4 R 2.0

Hard Disk: 1TB ST1000DM03-ATA

IV. OUTPUT

It is defined as the ratio of the number of Input images that are incorrectly classified as a Classified object from the total number of images taken as input. The error rate is formulated as given below,Classification accuracy is defined as the ratio of the number of objects that are correctly classified to the total number of Images. The formula for classification accuracy is defined as follows,

$CA = Correctly\ classified\ objects$ *100 -> (5)

$No.of\ Input\ Images$

$\boldsymbol{ER} = [\ IICC] * 100$ -> (6)

n

From (22), '$\boldsymbol{ER}$' denotes an error rate, $IICC$ indicates a number of images incorrectly classified and 'n' denotes the total number of images. The error rate is measured in percentage (%).

No of Input Images	Error Rate (%)		
	DCT-HED	SLR	Rough set
10	76.5	78.1	80.1
20	76.7	78.3	80.4
30	76.9	78.5	80.6
40	77.8	78.9	80.8
50	77.9	79.0	81.1
60	78.0	79.2	81.3
70	78.1	79.3	81.5
80	78.3	79.4	81.7
90	78.6	79.6	81.8
100	78.9	79.9	81.9

From (9),CA denotes classification accuracy and it is measured in terms of percentage (%).

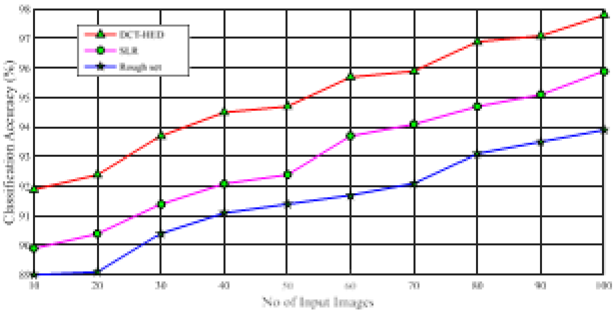
No of Input Images	Classification Accuracy (%)		
	DCT-HED	SLR	Rough set
10	91.9	89.9	89.0

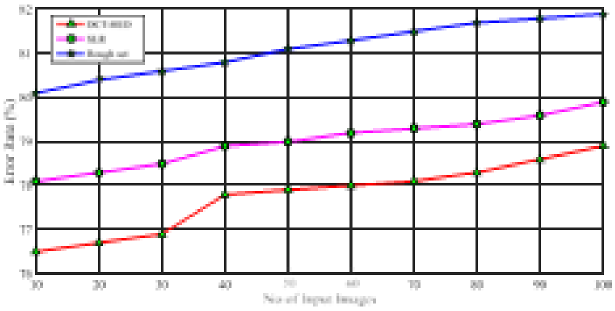
Let us Consider 10 input Images. The number of correctly Classified objects is considered as Input from the 10 objects, the numbers of correctly classified objects are measured Classification time

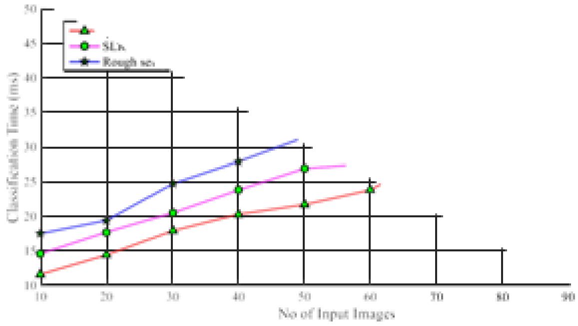
No of Input Images	Classification Time (ms)		
	DCT-HED	SLR	Rough set
10	11.6	14.6	17.5
20	14.4	17.7	19.4
30	17.9	20.5	24.7
40	20.3	23.8	27.9
50	21.7	26.9	31.4
60	23.8	27.6	34.7
70	29.1	34.4	37.9
80	31.4	37.7	39.2
90	34.3	39.1	43.5
100	37.8	41.8	45.7

Classification time is defined as an amount of time taken to classify the object in input images which is measured in terms of milliseconds (ms).

$classification\ time = No.\ of\ input\ images *$
$time\ (classifying\ one\ object)$ -> (6)







V. CONCLUSION

I present a method for text line recognition that employs two ANNs interconnected by the dynamic programming algorithm. The primary motivation for the proposed approach is to solve the per character segmentation task as the language-independent one. As data acquisition is an obstacle for training ANNs for different languages, we utilize only the synthetic training data in our central experiment. Achieve the highest recognition accuracy in comparison with previously published results of several LSTM-based and algorithmic methods. Moreover, we would like to mention that the recognition accuracy of our framework in images with names and other dictionary words can be improved significantly by using the language model post processing. We demonstrate the transferability of the segmentation network to different scripts if connected with the appropriate recognition ANN. To justify the applicability of the suggested light-weight classifier, we experiment with the classic MNIST dataset and acquire the results comparable with the state-of-the-art ones. To examine the segmentation method, we show that the segmentation networks trained on the data with different alphabets perform almost equally on different datasets. We employ synthetic data for this experiment as we need per character segmentation ground truth. To conclude, our framework demonstrates the powerful capabilities of employing the FCNs for text line segmentation and of using extremely light- weight ANNs for camera captured image recognition.

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