International Journal of Psychosocial Rehabilitation, Vol. 24, Issue 08, 2020
ISSN: 1475-7192

DEVANAGARI HANDWRITTEN CHARACTER RECOGNITION METHODS AND ANALYSIS

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Abstract

Presently these days recognizing the handwritten character recognition is getting high essentialness in light of various applications like educational field, digitized signature verification, bank processing, postal code acknowledgment, electronic library and so on. exceptionally less work is ac-counted in the research of Devanagari hand written character acknowledgment, so that there is an enormous extent of research right now. Some potential challenges adding to the unlawful execution of different frameworks for seeing deciphered characters are: various shapes, broken characters, various tendencies and measures, and so on. To overcome these types of issues, initially, we introduce a pixel intensity histogram based feature for the special character recognition, it identifies the special symbols and characters and different types of characters. Further, we used selection process done by improved rule based feature set selection algorithm. Dataset is collected and with help of this proposed improved rule based feature set selection algorithm, the accuracy of character identification is improved. Further, we use recurrent-artificial neural network classifier for classification and recognition process to classify different types of handwritten characters. The performance of proposed model is compared with the existing designs in terms of higher accuracy and speed in classification and recognition.

Keywords: *artificial neural network, a pixel intensity, improved rule based feature set selection algorithm, devanagari hand written character*

Introduction

Over couple of years, profound learning approaches have been effectively applied to different regions, for example, picture arrangement, discourse acknowledgment, malignancy cell recognition, video search, face location, satellite symbolism, perceiving traffic signs and so on. Character acknowledgment is one of the regions where AI strategies have been broadly tested.

The upper side of a character is termed as "shirorekha". In view of this shirorekha each character is separated into three particular parts. The segment in the upper part of shirorekha is called upper modifier, character next to shirorekha is called middle modifier and below that is lower modifier. Additionally, few characters consolidate to frame another character set called joint characters. Example is shown below:

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Received: 18 Apr 2020 | Revised: 16 May 2020 | Accepted: 21 Jun 2020

Fig. 1. Representing three strips of a word

Character acknowledgment is where the machine distinguishes and perceives the characters from a book picture and changes over that prepared information into a code which is comprehended by the machine. It is named as optical character acknowledgment (OCR) as they manage characters using optical devices and store them digitally for later use.

NEURAL NETWORK

Profound neural networks have demonstrated to be using the best decision making algorithms in many areas including character acknowledgment. Here we propose a procedure to perceive written by hand Devanagari characters utilizing profound convolutional neural systems (DCNN) which are one of the ongoing methods received from the profound learning network.

We tested the ISIDCHAR database given by (Information Sharing Index) ISI, Kolkata and V2DMDCHAR database with six distinct designs of DCNN to assess the presentation and furthermore examine the capabilities of the strategies portrayed by neural network. A layer-wise system of DCNN has been utilized that assisted with accomplishing the most noteworthy acknowledgment exactness and furthermore get a quicker assembly rate. [1]

This paper discusses advancement of matrix based technique which is mix of picture centroid zone and zone centroid zone of individual character or numerical picture. For extraction framework, zone based methodology is used and singular character or numerical picture is isolated into n equivalent measured lattices or zones and the point of separation of all pixels concerning picture centroid or matrix centroid is figured. picture centroid and zone centroid approaches, registers normal separation of all pixels present in every plane with respect to pictures centroid just as zone centroid. which gives highlight vector of size 2xn highlights.

SYSTEM MODEL AND ALGORITHMS

System Model

Our proposed system model is shown in fig. 2. initially, introduces a pixel intensity histogram based feature for the special character recognition and further selection process done by improved rule based feature set selection algorithm. Then, we use recurrent-artificial neural network (RANN) classifier for classification and recognition process. Here RANN classifiers, classifies and recognizes varieties of handwritten characters. Generally, the handwritten characters are classified two types, printed and handwritten.

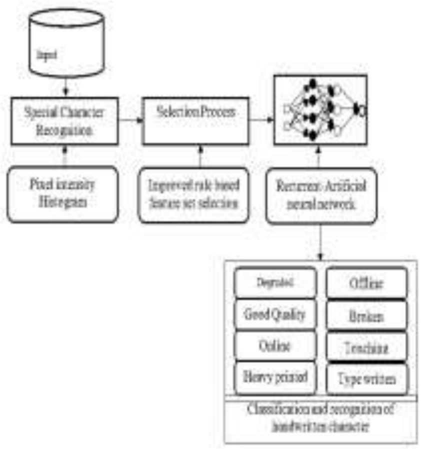

Fig. 2. Proposed System model

Special Character Recognition Using Pixel Intensity Histogram

An image histogram is a diagram of pixel intensity/power (on the x-hub) versus number of pixels (on the y-hub). Numerous dim levels can be joined into bunches so as to decrease the quantity of individual qualities on the x-hub. Advanced pictures are made out of two-dimensional number exhibits that speak to singular segments of the picture, which are called picture components, or pixels. The pixel esteems in highly contrasting pictures can be either 0 (dark) or 1 (white). In the event that n bits are utilized to speak to a pixel, at that point there will be 2n pixel qualities running from 0 to (2n - 1). Here 0 and (2n - 1) compare to high contrast, individually, and all other middle of the road esteems speak to shades of dim. Such pictures are said to be monochromatic. A picture histogram is a diagram of pixel force (on the x-pivot) versus number of pixels (on the y-hub). The x-hub has all accessible dim levels, and the y-hub demonstrates the quantity of pixels that have a specific dim level worth. Various dim levels can be consolidated into bunches so as to diminish the quantity of individual qualities on the x-hub. The Pixel Intensity Histogram (PIH) include vector is processed from the picture utilizing angle locators. Right now, pixel is convolved with the basic convolution part as follows:

$$G_a = f(a+1,,b) - f(a-1,b)$$
$$G_b = f(a,b+1) - f(a,b-1)$$

G_a and G_b are the flat and vertical segments of the angles, separately. In our tests, the HOG descriptor is determined over rectangular squares (PIH) with non-covering squares.

To disregard negative slope bearings, the scope of inclination directions is characterized between 0^0 and 180^0. The angle extent M and the inclination direction θ are determined by,

$$M(a,b) = \sqrt{G_a^2} + G_b^2$$

$$\theta(a,b) = \tan\frac{G_b}{G_a}$$

After this, histograms are registered from the events of arranged angles across enormous structures (hinders) of the picture. The slope directions are put away into 9 direction. The blend of the histograms from each square speaks to the element descriptor. The element vector size of the PIH descriptor relies upon the chose quantities of squares and canisters. It has been demonstrated that the exhibition of the HOG descriptor relies for the most part upon the quantity of squares. Finally, the component descriptors are standardized by applying the standardization as follows:

$$H_c = \frac{H_c^2}{\sqrt{|H_c|^2 + \varepsilon}}$$

$$L(a,b,\sigma) = G(a,b,\sigma) * I(a,b)$$

$$G_a = L(a+1,b,\sigma) - L(a-1,b,\sigma)$$

$$G_b = f(a,b+1,\sigma) - f(a,b-1,\sigma)$$

To apply smoothness, the dark force distinction between two pixels from a similar set is near zero in close by neighbourhoods with probability close to 1. To apply local contrast, the difference between a pair of pixels from different set is greater than the difference between a pair of pixels from the same set. Mathematically,

$$\underset{q \in B \cap N_s(P)}{MIN} I(q) \quad \underset{q \in B \cap N_s}{MAX} I(q) < D_c$$

with likelihood near 1, where D_s is a huge positive number regarding D_s .

A. Selection Process Using Improved Rule Based Feature Set Selection Algorithm

A standard based classifier comprises of a lot of IF-THEN guidelines, and every combination of characteristic worth sets (which will be called highlight esteem pair in the present paper) in the precursor of the standard, trailed by a class name in the standard subsequent. The if-and-then statement as follows:

$$IF \;\; Weight = heavy \quad AND \;\; radar = Selects\ the\ \ pixel$$
$$THEN \;\; Selects\_vehicles = yes$$

Given an objective case to be grouped, if the state of the standard precursor (i.e., all the component esteem test) remains constant, at that point it is said that the standard predecessor is fulfilled. This additionally implies that the data is secured by that standard. A standard R is regularly assessed by its inclusion and precision. Given a dataset D with class names, assume, the quantity of occasions secured by the standard R is the quantity of cases ordered effectively, and |D| is the absolute number of cases in the dataset D then the inclusion of the standard R is characterized as:

$$Coverage = \frac{N_{Covers}}{|D|}$$

In this manner, the accuracy of the standard R is characterized as follows:

$$Accuracy = \frac{N_{Covers}}{N_{Covers}}$$

The fundamental prism calculation prompts secluded characterization controls straightforwardly from the preparation set, in which the component esteem sets are viewed as the discrete message in data hypothesis. As indicated by the essential standard of data hypothesis, the measure of data about an occasion in message i is characterized in as follows:

$$I(t) = \log_2\left(\frac{\Pr oability\ of\ \ event\ \ after\ \ get\ the\ \ message}{\Pr oability\ \ of\ \ event\ \ before\ get\ \ message}\right) bits$$

CLASSIFICATION OF HAND WRITING AND RECOGNITION PROCESS RECURRENT- RANN CLASSIFIER

A small artificial neural network (ANN) is a network of small processing units or nodes which are interconnected to each other. There are two basic types of ANNs: cyclic and acyclic. Non-recurrent ANN does not allow rotation connections known as feed forward neural networks (FNNs). Recurrent ANN, on the other hand, is called feedback, repetition, or continuous neural network (RNN). Here, the number of hidden layers is two and contains the K and L units that use the hyperbolic tangent (tan h) function for processing. The network has SSC (single stroke classifier) layer, output layer size 2, and SBC (stroke pair classifier). The activation output, activation function used in RNN is similar to the standard neural network. The number of input nodes corresponds to the variable number of the input vector. The number of input nodes in the pattern recognition system usually is determined by the number of feature extracts. Simple computations require fewer hidden units and as the computation gets complex more number of hidden units are required. Learning rate has been chosen in a range [0.01 to 0.1]. The purpose of determiner is to determine the output of the neural network by making some operation on the output and then compare the output with the desired output data and 4 output neurons for BCNN. The output vector will be compared with target vector (desired). Each element of target vector is a binary value (-1 or 1). The outputs of this network are calculated according to the following equations:

$$Y = F\left(Base1 + \sum_{i=1}^{10}\left(\overline{W}_{ji}, X_i\right)\right) \quad (1)$$

$$Z = F\left(Base\,2 + \sum_{i=1}^{m}\left(\overline{W}_{ji}, Y_i\right)\right) \quad (2)$$

$$F(Y) = \frac{1-e^{-y}}{1+e^{-y}} \quad (3)$$

$$\frac{df}{dy} = 0.5X\left(1 - f(y)^2\right) \quad (4)$$

The hidden layer weight is computed as:

$$\overline{W}_{new} = W + \lambda_i SY \times Y \quad (5)$$

The output layer weight is computed as:

$$\overline{W}_{new} = W + \lambda_i So \times Z \quad (6)$$

where,

$$So = (D - Z) \times \frac{dz}{do} \quad (7)$$

$$SY = W_{ij} \times \frac{df}{dyj} \times So \quad (8)$$

Where, F(Y) is the transfer function of the neurons. Base1 is the weight of the bias in the input layer. Base2 is the weight of hidden layer. W is the weight connection vector between the input layer and the hidden layers W is the weight connection vector between the hidden layer and the output layers Y is the output of the hidden layer, X is input vector, Zi is the output vector of classifier *So*, is Error one type of recognized handwriting from hidden layers *SY* is another type of recognized hand-writing in output layers.

RESULT AND DISCUSSION

The MNIST data set contains handwritten numerical images, divided into 60,000 examples for the training set and 10,000 examples for the test. All digital images are normalized in size and centered on a fixed size image of 28 × 28 pixels. CPAR-2012 database developed by the System Group Noida (CPR's Pattern Analysis and Recognition Center), has been available to the research community since 2012 [2]. Dataset details and training samples and error rate given below:

TABLE I. TRAINING SAMPLES

Dataset	Training Samples	Test Samples	Configuration of neural net	Recognition time of dataset especially training	Percentage error
MNIST handwritten digit	50000	10000	784-100-10	4546 sec	2.22
MNIST handwritten digit	50000	10000	784-200-100-10	9471 sec	2.15
ISI digit	18000	3500	784-100-10	1524 sec	3.31
ISI digit	18000	3500	784-200-100-10	3239 sec	3.17
CPAR-2012 character	49000	29400	784-100-49	3903 sec	21.54
CPAR-2012 character	49000	29400	784-200-49	8334 sec	18.6
CPAR-2012 numeral	26250	8750	784-200-11	5422 sec	2.53
CPAR-2012 numeral	26250	8750	72-100-11	2153 sec	2.8

In this section, we analysis the performance of our proposed RANN classifier comparing with existing methodologies. Here, we analysis the accuracy of following criteria's, consonants and vowels, compound characters, vowels modifiers.

Comparison studies of our proposed and existing methodologies:

Methods	Accuracy (%)
D-PSO	96.2
HDCD	97.5
MLP	98.9
RANN	99.2

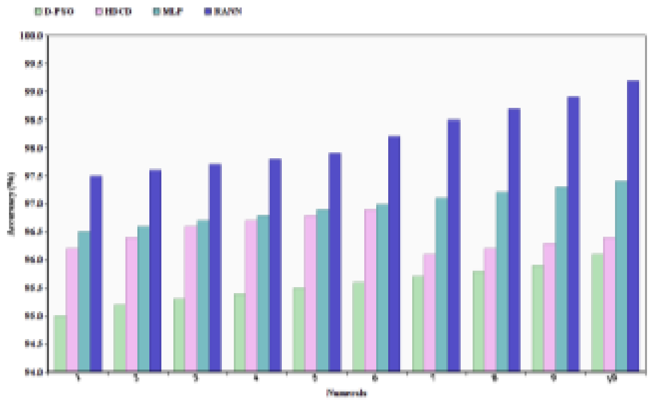

Fig. 3. Analysis of numerals

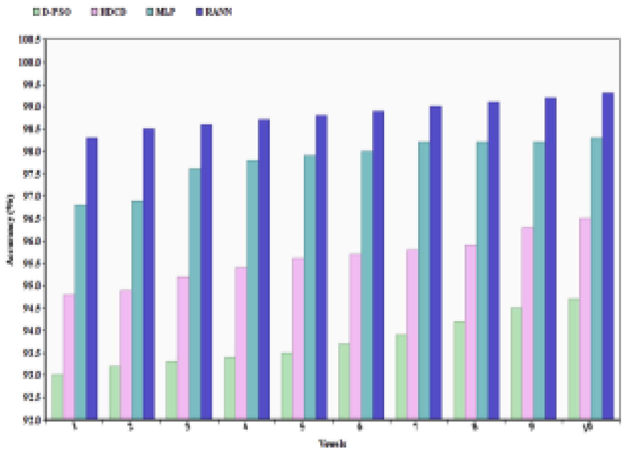

Fig. 4. Analysis of vowels

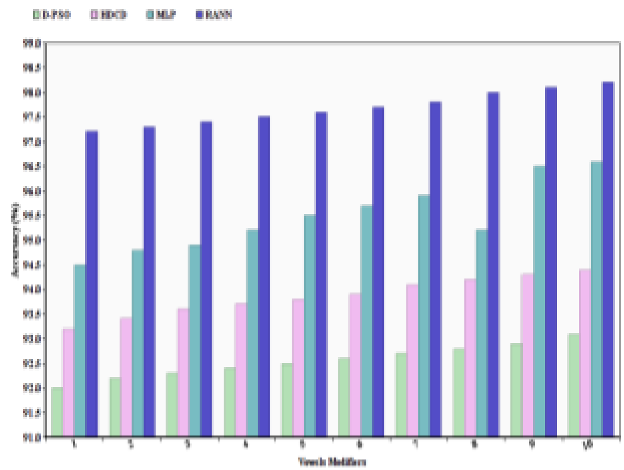

Fig. 4. Analysis of vowel modifiers

CONCLUSION

Initially, we characterized the special characters with help of pixel intensity Histogram based feature. Further, we selected the features sets based on the improved rule based feature set selection algorithm. Moreover, we recognized and classified the various handwritten characters with help of our proposed recurrent-artificial neural network (RANN) classifier. Moreover, comparing with other existing methodologies D-PSO, HDCD, MLP, our proposed RANN classifier is provides high accuracy.

ACKNOWLEDGMENT

We are very much thankful to our organization for providing all kind of logistic and other supports.

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