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User Identification Using HMM And ANN

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Abstract- The handwriting of a person is an important biometric attribute of a human being which can be used to authenticate human identity. A number of biometric techniques have been proposed for personal identification in the past. Handwriting by an authorized person is considered to be the "seal of approval" and remains the most preferred means of authentication. Handwritten recognition has been an active and challenging problem. Most of the traditional methods have two challenges, due to the large variations of written text and the dependency relationship between letters. First, in real applications, words may be written cursively, so it is hard to identify the words automatically. Even if the words are neat, different people may write the same words in different styles. Since there are large shape variations in human handwriting, recognition accuracy of handwritten words is very difficult. The method presented in this paper consists of image prepossessing, geometric feature extraction, neural network training with extracted features and verification. A verification stage includes applying the extracted features of test handwriting to a neural network which will classify it as a genuine or forged. To recognize the handwritten words, the proposed work combines Artificial Neural Network (ANN) and Hidden Markov Model (HMM).

Keywords— HMM, ANN

I. INTRODUCTION

In our society, traditional and accepted means for a person to identify and authenticate himself either to another human being or to a computer system is based on one or more of these three general principles, namely person is, person knows and person possesses. The handwritten letter is one of the ways to authorize transactions and authenticate the human identity compared with other electronic identification methods such as fingerprints scanning, face recognition and retinal vascular pattern screening [1-3]. The handwritings are referred as the primary means of identifying the signer of a written document based on the implicit assumption that a person's normal handwriting changes slowly and is very difficult to erase, alter or forge without detection [4]. It is easier for people to migrate from using the popular pen-and-paper handwriting to one where the handwritten handwriting is captured and verified electronically. The handwriting of a person is an important biometric attribute of a human being and is used for authorization purpose [5].

Handwriting recognition is the process of verifying the writer's identity by checking the handwriting against samples kept in the database. The result of this process is usually between 0 and 1 which represents a fit ratio (1 for match and 0 for mismatch) [6].As handwriting is the primary mechanism both for authentication and authorization in legal transactions, the need for efficient auto-mated solutions for handwriting verification has increased. Handwriting of different person has different stroke, tilt and other patterns. Each writing may comprise of different set of characters [7]. Thus, DWT is a suitable technique for detecting such features. The system is first normalized with respect to slant, skew, baseline location and height. A sliding window is used to transform a normalized handwritten text line into a sequence of feature vectors. The window is one pixel wide and shifted from left to right over a line of text. At each position of the window, five geometrical features of extracted [8].

A new classification model, which has never been used for handwriting verification, is proposed in this system. This model, has been used to solve classification problem since the last decade. This model is based on gradient and geometrical properties. Therefore, the majority of the parameterization techniques proposed in this paper, are based on these properties. These techniques are: contour measure (measure of widths and heights of the handwriting contour), contour following (handwriting contour measure in polar coordinates), region grouping (grouping theletter stroke in regions according a connection criterion) and direct image (concatenation of all the rows of the matrix that represent

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the signature image). In order to train and evaluate the proposed system, separate database has been maintained, one for the training and other one for the testing/verification [9-10].

The standard DWT has proved to be very useful tool handwriting recognition although they present a poor discriminative power. On the contrary neural networks have been recognized as powerful tools for classification, but they are less efficient to model temporal variations than existing techniques. This paper has been inspired from the above mentioned work [11-14]. The literature explains many high accuracy recognition systems for separated handwritten numerals and characters. However feature extraction based on local and global geometric features of the character skeleton has not been investigated much [15]. The algorithm proposed concentrates on the same. It extracts different line types that forms a particular alphabet. It also concentrates on the positional features of the same. The feature extraction technique explained was tested using a Neural Network which was trained with the feature vectors obtained from the system proposed.

Section I contains the Introduction .Section II contains the related work. Section III contains the proposed Methodology. Section IV contains the proposed work. Section V describes results and discussion .Section VI concludes research work with future directions

II. RELATED WORK

Alfa Ryano Yohannis, Teny Handhayani,,Lely Hiryanto use GLCM for feature extraction ,Bootstrap for classification and obtained 70% accuracy for signature,90% accuracy for Handwriting. J Ignacio Toledo, Sounak, Josep use Recurrent Neural Networks for handwriting recognition. Partha S Mukherjee ,Ujjwal Bhattacharya, Swapan K Paruti use Hybrid layered architecture consisting of three networks CNN (conventional neural networks), RNN(Recurrent neural network), CTC(Connectionist temporal classification). For Devanagiri & Bangla online unconstrained handwritten words and obtained accuracy of 84.4%.

HMM training algorithms are based on likelihood maximization, which assumes correctness of the models. But HMM implies poor discrimination ability whereas, on the other hand NN has superior discriminative ability. Hence to take the advantages of both the techniques the proposed method uses Hybrid HMM and NN.HMM for training and ANN for classification.

III. METHODOLOGY

The proposed work uses Baum-Welch algorithm for training and Multilayer Perceptron (MLP) classifier for classification .

Baum-Welch is an iterative procedure for estimating from only X. It works by maximizing a proxy to the log likelihood, and updating the current model to be closer to the optimal model. Each iteration of Baum-Welch is guaranteed to increase the log-likelihood of the data. But of course, convergence to the optimal solution is not guaranteed.

A Multilayer perceptron(MLP) is a class of feed forward artificial neural network. An MLP consists of at least three layers of nodes. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called back propagation for training. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron. It can distinguish data that is not linearly separable.

IV. PROPOSEDWORK

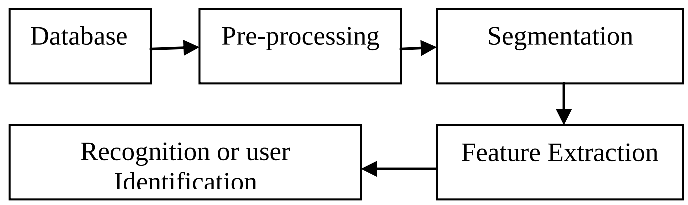

Fig 1: Block diagram of proposed system of handwriting recognition system.

PREPROCESSING

In the pre-processing the handwritings are scanned in gray. The purpose of this phase is to make handwriting standard and ready for feature extraction. The pre-processing stage improves quality of the image using four stages of morphological operation; these four operations are explained in brief in the following stages.

- Edge detection
- Image dilation
- Image filling
- Noise removal.

Edge detection:

Canny Edge Detection: The purpose of edge detection in general is to significantly reduce the amount of data in an image, while preserving the structural properties to be used for further image processing. Even though it is quite old, it has become one of the standard edge detection methods and it is still used in research. The aim of Canny Edge Detection was to regard of following criteria:

1. Detection: The probability of detecting real edge points should be maximized while the probability of falsely detecting non-edge points should be minimized. This corresponds to maximizing the signal-to-noise ratio.
2. Localization: The detected edges should be as close as possible to the real edges.

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3. Number of responses: One real edge should not result in more than one detected edge (one can argue that this is implicitly included in the first requirement).

In this research work, six steps have been followed to improve the existing algorithms of edge detection. The first one is make low rate of errors and edges which are taken place in the images should be retained without missing and edge method should not response for non-edges of the image. The second step is to identify an edges of the image which are the pixels between detector and the actual edge and these edges must be at a minimum. The third step is to detect only one response to a single edge to eliminate the multiple responses to an edge [16].

Based on the above discussed steps, the canny edge detector is chosen in this research work to smoothes the image to eliminate the noise terms or pixels in the image. For accurate edge detection gradient method is used to highlight the regions using spatial derivative operation are shown in equation (1) and (2)

$$G(m,n) = \sqrt{g_m^2(m,n) + g_n^2(m,n)} \quad (1)$$

$$\phi(m,n) = \tan^{-1}[\frac{g_m(m,n)}{g_n(m,n)}] \quad (2)$$

The calculation at that point tracks along these locales and smothers any pixel that isn't at the most extreme (non-greatest concealment). The slope cluster is currently additionally diminished by hysteresis. Hysteresis is utilized to track along the rest of the pixels that have not been stifled. Hysteresis utilizes two edges and if the extent is beneath the main edge, it is set to zero. In the event that the extent is over the high edge, it is made an edge [17].

With a particular ultimate objective to execute the attentive edge discoverer estimation, a movement of steps must be taken after. The underlying advance is to filter through any commotion in the main picture before endeavoring to discover and recognize any edges. Besides, in light of the fact that the Gaussian channel can be figured using a clear cover, it is used just in the Canny computation. Once a proper cover has been found out, the Gaussian smoothing can be performed using standard convolution procedures. A convolution cover is for the most part significantly tinier than the honest to goodness picture [18]. In this manner, the cloak is slid over the photo, controlling a square of pixels without a moment's delay. The greater the width of the Gaussian cover, the lower is the locator's affectability to racket. The impediment botch in the perceived edges in like manner augments imperceptibly as the Gaussian width is extended

In the wake of smoothing the picture and killing the clamour, the following stage is to discover the edge quality by taking the inclination of the picture. The Sobel administrator plays out a 2-D spatial angle estimation on a picture. At that point, the estimated outright inclination greatness (edge quality) at each point can be found. The Sobel administrator utilizes a couple of 3x3 convolution veils, one assessing the slope in the x-bearing (sections) and the other evaluating the inclination in the y-course (lines). The size, or edge quality, of the inclination is then approximated utilizing the equation: |G| = |Gx| + |Gy|.

The bearing of the edge is registered utilizing the angle in the x and y headings. Be that as it may, a blunder will be produced when sumX is equivalent to zero. So in the code there must be a confinement set at whatever point this happens. At whatever point the angle in the x bearing is equivalent to zero, the edge course must be equivalent to 90 degrees or 0 degrees, contingent upon what the estimation of the slope in the y-heading is equivalent to. On the off chance that GY has an estimation of zero, the edge heading will measure up to 0 degrees. Generally the edge bearing will meet 90 degrees. The recipe for finding the edge bearing is simply: Theta = invtan (Gy / Gx)

After the edge bearings are known, non-maximum concealment currently must be connected. Non-maximum concealment is utilized to follow along the edge in the edge bearing and stifle any pixel esteem (sets it equivalent to 0) that isn't thought to be an edge. This will give a thin line in the yield picture. At last, hysteresis is utilized as a methods for disposing of streaking. Streaking is the separating of an edge shape caused by the administrator yield fluctuating above and underneath the limit. In the event that a solitary limit, T1 is connected to a picture, and an edge has a normal quality equivalent to T1, at that point because of clamor, there will be examples where the edge plunges beneath the edge. Similarly it will likewise reach out over the limit influencing an edge to resemble a dashed line. To keep away from this, hysteresis utilizes 2 limits (T1 and T2), a high and a low [19-25]. Any pixel in the picture that has esteem more noteworthy than T1 is dared to be an edge pixel, and is set apart in that capacity promptly. At that point, any pixels that are associated with this edge pixel and that have an esteem more prominent than T2 are additionally chosen as edge pixels. In the event that you consider following an edge, you require a slope of T2 to begin yet you don't stop till you hit an inclination beneath T1 as per equation (3).

$$Tht(m,n) = \begin{cases} Th(m,n) & if\ Th(m,n) > t \\ 0 & otherwise \end{cases} \quad (3)$$

T

The output of handwriting after applying the canny detect is shown in Fig.2.

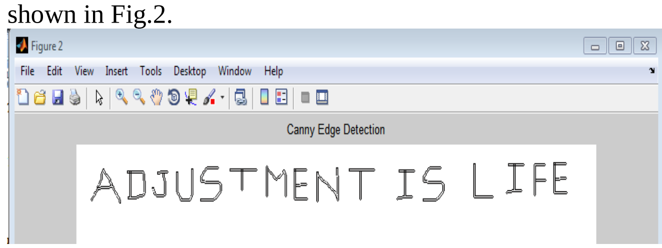

Fig.2. Canny edge detection output for given handwriting

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Image dilation:

The dilation of an image f by a structuring element s (denoted f ⊕ s) produces a new binary image g = f ⊕ s with ones in all locations (x,y) of a structuring element's origin at which that structuring element s hits the input image f, i.e. g(x,y) = 1 if s hits f and 0 otherwise, repeating for all pixel coordinates (x,y). Dilation has the opposite effect to erosion -- it adds a layer of pixels to both the inner and outer boundaries of regions. Results of dilation or erosion are influenced both by the size and shape of a structuring element. Dilation and erosion are dual operations in that they have opposite effects. Let c denote the complement of an image f, i.e., the image produced by replacing 1 with 0 and vice versa. Fig.3.shows Image dilation output .

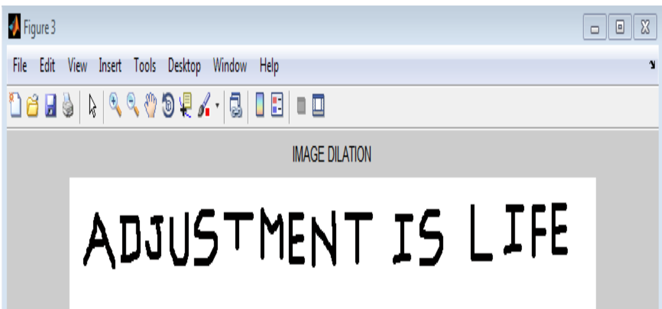

Fig.3: Image dilation output

Image filing:

In vision, filling-in phenomena are those responsible for the completion of missing information across the physiological blind spot, and across natural and artificial scotomata. There is also evidence for similar mechanisms of completion in normal visual analysis. Classical demonstrations of perceptual filling-in involve filling in at the blind spot in monocular vision, and images stabilized on the retina either by means of special lenses, or under certain conditions of steady fixation. For example, naturally in monocular vision at the physiological blind spot, the percept is not a hole in the visual field, but the content is "filled-in" based on information from the surrounding visual field. When a textured stimulus is presented centered on but extending beyond the region of the blind spot, a continuous texture is perceived. This partially inferred percept is paradoxically considered more reliable than a percept based on external input.

A second type of example relates to entirely stabilized stimuli. Their color and lightness fade until they are no longer seen and the area fills in with the color and lightness of the surrounding region. A famous example of fading under steady fixation is Troxler's fading. When steadily fixating on the central dot for many seconds, the peripheral annulus will fade and will be replaced by the color or texture of the background. Since the adapted region is actively filled-in with background color or texture, the phenomenon cannot be fully explained by local processes such as adaptation.

There is general agreement that edges play a central role in determining the apparent color and lightness of surfaces through similar filling-in mechanisms. However, the way in which their influence is performed is still unclear. Two different theories have been put forward to explain the filling-in completion phenomenon .as showing Fig.4 .shows Image filing output .

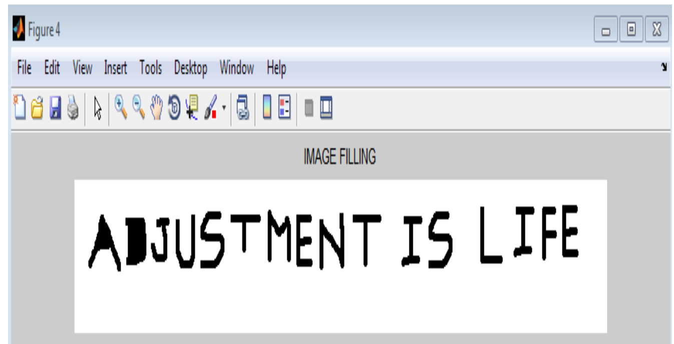

Fig 4: Image filling

Noise removal:

Median filtering is a nonlinear method used to remove noise from images. It is widely used as it is very effective at removing noise while preserving edges. It is particularly effective at removing 'salt and pepper' type noise. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighboring pixels. The pattern of neighbors is called the "window", which slides, pixel by pixel, over the entire image. The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value.

Feature extraction:

For the feature extraction process, the proposed work used the basic HMM model and in this approach, we have selected two conditions namely gradient based and geometric feature based approach. After extracting the features of handwritten recognition along text with letters, the derivative has been measured with respect to the generic parameters of the HMM model and it involves gradient descent to update the parameters iteratively as per the equation (4)

$$i^{j+1} = i^{(j)} - \eta \frac{dy^{(j)}}{dx} \tag{4}$$

Where is the iteration rate, the parameters of the HMM are probabilities and performing the gradient descent to optimization to negative estimation of the image and its values are lies between 0 to 1 and to measure new variables of the gradient descent using the equation (5)

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$$\beta_{jt} = \frac{\exp(x_{jt})}{\sum_t \exp(x_{jt})} \quad (5)$$

In case of geometric based feature extraction process it is evaluated using euler method of extraction of geometric features of the handwriting text and for the analysis of skewness and straightness of the handwritings gradient method is adopted. In the HMM model geometry is major role in the research work to measure the global context and to evaluate the local features and for efficient smooth the curves. Both methods were implemented on the resultant of the HMM, where in HMM for the feature extraction Log-Likelihood similarities (LLS) is operated and which is given by equation as follows

$$LLS = 2\sum_{0}^{k}(H(k) - H(sumofrows(k) - H(sumofcolumns(k))$$

where H is shannon's entropy and it is computed by using

$$H = \sum_{0}^{k}\log(\frac{f(i,j)}{sum(k)})$$

and it is function of H=function(k){N=sum(k); return(sum(k/N*log(k/N+(k==0)))}

Segmentation:
Segmentation of hand written text document into individual character or digit is an important phase in handwritten document analysis, recognition and many other areas.in order to segment text from a given input document image, it is necessary to detect all the possible text regions. In the case of printed scripts, segmentation is a relatively simple task. In the case of overlapped scripts, broken characters, connected characters, loosely configured characters, and mixed scripts, segmentation is difficult. The method used for segmentation is region based segmentation.

Division of pictures is pivotal to our comprehension of them. Thusly much exertion has been given to formulating calculations for this reason. Since the sixties an assortment of methods have been proposed and striven for fragmenting pictures by distinguishing areas of some regular property. These can be arranged into two primary classes:

i. Merging algorithms: in which neighbouring regions are compared and merged if they are close enough in some property.
ii. Splitting Algorithms: in which large non-uniform regions are broken up into smaller areas which may be uniform.

There are algorithms which are a combination of splitting and merging. In all cases some uniformity criterion must be applied to decide if a region should be split, or two regions merged. This criterion is based on some region property which will be defined by the application, and could be one of many measurable image attributes such as mean intensity, colour etc. Uniformity criteria can be defined by setting limits on the measured property.

Neural Networks Approach:
Neural Networks (NNs) offer a new group of nonlinear algorithms for feature extraction using hidden layers, and classification using multilayer perceptrons. An Neural network is an information processing model that is motivated by the biological nervous systems, like the brain, to process information. The key element of this model is the novel configuration of the information processing system. It consists of a large number of highly interconnected processing elements (neurons) working in unity to solve particular problems. An neural network model was used to classify the handwritten text from the input

A multilayer perceptron (MLP) is a class of feed forward artificial neural network. An MLP consists of at least three layers of nodes. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called back propagation for training. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron. It can distinguish data that is not linearly separable.

NNs therefore are highly suited to modelling global aspects of handwritten text. The proposed system in uses structure features from the input contour, modified direction feature and additional features like surface area, length skew and centroid feature in which a signature is divided into two halves and for each half a position of the Centre of gravity is calculated in reference to the horizontal axis.

Algorithm:
Step 1: select the handwriting image for processing.
Step 2: process the image with image pre-processing.
Step 3: extract the handwriting image feature extraction
Step 4: classify the handwritten characters based on the features extracted.
Step 5: count the number of handwriting text in the input image.
Step 6: display the number of characters and save in the separate text file with the appropriate matching handwritten characters.
Step 7: identify and authenticate the user.

V. Results and Discussion

The paper will present experimental results with two applications: Identifying the user and counting the number of characters in the given sentence.

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The proposed work is designed and validated using Matlab2014a and the designed handwriting recognition tool is user friendly to operate on each module. The Graphical User Interface (GUI) has been created with different switches; each switch is for one operation. From the database consisting of 880 samples, any one sample is subjected to the proposed GUI system for further operations. The experimental results show that the proposed method has achieved 100% recognition accuracy by training 600 samples as shown in table 1.
The figures below show the stepwise execution.

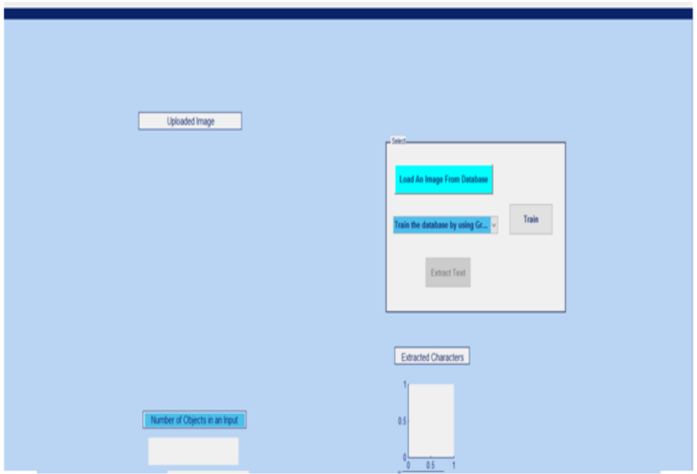

Fig. 5: Window for uploading the image from trained database.

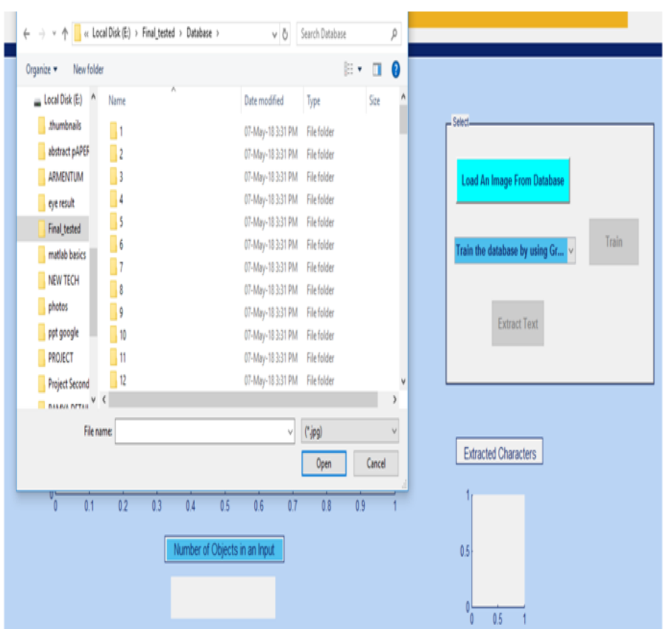

Fig 6: Selecting the image from the database

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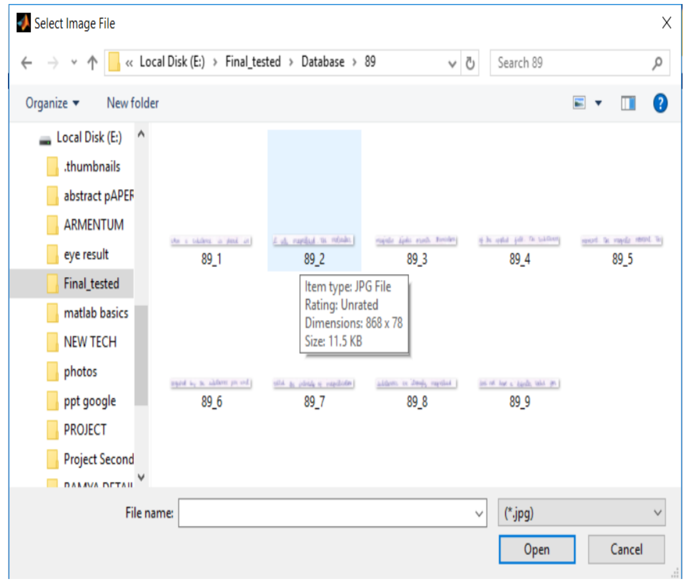

Fig 7: Selecting one handwritten instance of one user from database

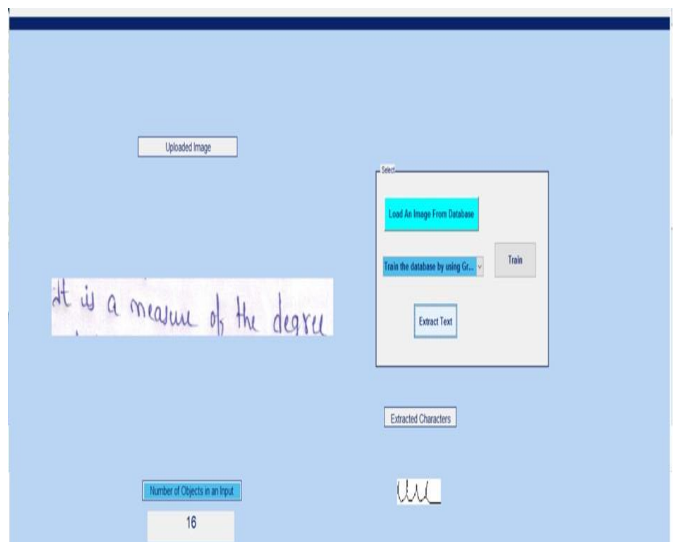

Fig 8. Result showing the number of characters in selected database

Table 1: Accuracy for Handwriting recognition using HMM and NN

No of trained instances	No of testing instances	No of mismatched instances	Accuracy in %
100	780	650	16.66
200	680	400	41.17
300	580	280	51.72
400	480	180	62.5
500	380	110	96.42
600	280	00	99%

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From the table it is observed that by training 600 samples we achieved 100% accuracy, we need to find an efficient algorithm which will give 100% accuracy by training only few samples.

VI. CONCLUSION AND FUTURE SCOPE

The proposed work identifies 100 user's English handwritings Using HMM and ANN. 9 instances of each user are taken, thus there are total 880 instances of which 600 instances (6 instances of each user) are used for training and remaining are kept for testing. By using Baum-welch algorithm in HMM for training and MLP classifier in ANN for recognition the proposed work give 99% recognition accuracy by training 600 samples. Thus there is need to find an efficient algorithm which will give 100% accuracy by training only few samples.

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