

# Hidden Markov Model Based Odia Numeral Recognition Using Moment and Structural Features



**Om Prakash Jena, Sateesh Kumar Pradhan, Pradyut Kumar Biswal, Alok Ranjan Tripathy, Sradhanjali Nayak**

**Abstract:** Optical character recognition (OCR) is a strategy to perceive character from optically checked and digitized pages. OCR plays an important role for Indian script research. The official language of the state Odisha is Odia. OCR face an incredible difficulties to recognize Odia language due to similar shape characters, their complex nature, the complicated way in which they combine form to compound character, use of Matra etc. Each character and numbers are passed through several modules like binarization, noise removal, segmentation, line segmentation, word segmentation, skeletonization, deskewing, thinning, thickening. The input picture is standardized to a size of 50 x 50 2D pictures. HMM is a stochastic process which has utilized in various applications for example speech recognition, Handwriting recognition, Gesture recognition. In this paper we utilized HMM to recognize the Odia character and numbers. Hidden Markov Model have many advantages such as resistant to noise, handle contrast recorded as a hard copy and the HMM devices are effectively accessible. In our proposed method we have developed an efficient recognition algorithm using Hidden Markov model based on moment based and structural feature to recognize Odia characters and numerals.

**Keywords:** Odia Numerals, Hidden Markov model, Moment based Feature, Structural Feature.

## I. INTRODUCTION

The mechanical or electronic change of composed by printed or hand content into machine encoded content is known as Optical character recognition (OCR). OCR is the specialty of perceive character by PC that on optically sifted and digitized pages of substance. These pages can be on the

web or disconnected, rely on the content written in contact touchy surfaces or on a bit of paper. To make simple to prepare the yield of OCR can be ASCII encoded or Unicode type. As a result of its wide scopes of uses, OCR is popular not only in academic fields but also in industrial fields. OCR can be utilized in postal robotization, smart library maintenance, bank check preparing, and programmed information section. In India multiple languages are spoken and used. There are more than 1600 language are found from which some are official and some are unofficial. These languages are written in different script including Odia. Out of those language English is globally used and very popular so that OCR is well developed using this language. Odia language is used by more than 40 billion people. The state like Odisha, Andhra Pradesh, Jharkhand, Chhattisgarh and West Bengal use the ODIA language. By the Government of India as ODIA is declared as the classical language.

### A. Properties of Odia Character

An Odia scripts are derived from brahmi scripts. The Odia content is round in nature and there is no going with line at the highest point of a character. It is trusted that the round shape developed from the need to compose a pointed stylus on palm leaves, which tends to tear for flat or vertical strokes. There are 49 alphabets in Odia scripts among them 11 are Vowels, 34 are consonants. Vowels may show up in unadulterated structure as an autonomous vowel in any piece of a word or these can be connected as modifiers to the top, base, left or right-half of consonants.

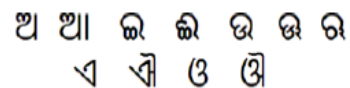


Fig. 1. Odia Vowels

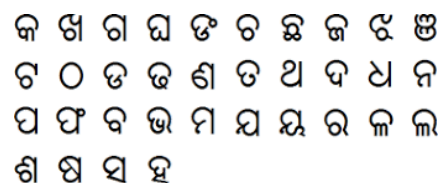


Fig. 2. Odia Consonants

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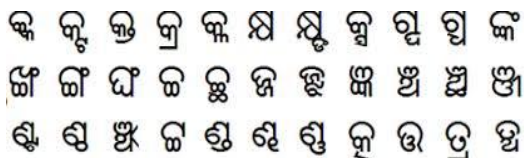


Fig. 3. Odia Conjuncts



Fig. 4. Odia Digits

II. RECENT WORKS

The author designed a model to recognize Odia numerals utilizing Low unpredictability Neural classifier by taking the component slope estimation, arch calculation, highlight vector age and measurement decrease of the element vector and found the accuracy 90.50%[1]. The author proposed a model to recognize printed Odia scripts using segmentation by taking the topological feature and stroke based features. Topological feature includes presence of openings and their number, places of gap as for the character bounding box, proportion of opening tallness to character stature. The accuracy for line segmentation is 97.7%, character recognition is 96.3%, and character segmentation is 97.2% [2]. Off-line Odia handwritten character was recognized by using Principal component analysis by taking the feature like gradient and curvature features and found the result up to 94.60% [3]. Author purposed Ant Miner Algorithm to recognize Odia script by using local and global features. Global feature includes circle, number of end focuses, even strokes, vertical strokes, angular strokes, aspect ratio and found the accuracy 90% [4]. Odia character was recognized by using neural network taking the structural feature such as round upper part, vertical line, gaps, run code level, run code value in vertical, number of open areas, gap position and the accuracy rate was influenced because of quality of comparable molded characters [5]. The author purposed a model to recognize off line Odia Character by using support vector machine taking the feature as element mean separation of line, mean point of line, mean separation section, and mean edge of section from focal point found the accuracy of 96.3% [6]. The author designed a model to recognize Odia printed document by using Line segmentation and word segmentation based taking the features based on zone of the character found the result 99.3% for line segmentation and 86.5% for word segmentation [7]. The author developed a model to recognize Text independent Odia script using SVM taking the curvature feature and found the accuracy up to 94% [8]. Author designed a model to recognize Odia handwriting numerals by using neural network taking the dimensional feature such as bounding box, normalization the gray scale image and found accuracy 94.81% [9]. The author purposed a method to recognize Odia script using SVM and KNN classifier by taking nearby paired example, focus symmetric neighborhood

parallel example, directional neighborhood outrageous example and using LBP feature with SVM classifier the performance of Odia script identification was found to be 84% [10]. Author developed a model for Odia script by using support vector machine and greedy partitioning by taking the directional feature such as meshing, horizontal, vertical, right, left and found the accuracy up to 95% [11]. Offline Odia character can be recognized using segmentation, neural network and back propagation by taking the statistical and geometrical, Structural features, hybrid feature and found the result up to 97.87% [12]. Author proposed a method for recognize Odia conjunct character using evolutionary algorithm by taking the binary feature and found the result for genetic algorithm was about 95.9% and back propagation neural network was 93.95% [13]. The author used HMM, Baum-Welch and Genetic Algorithm to recognize English character by taking the gradient feature, blocks and implementing the feature using forward algorithm found the accuracy up to 83.33% [14]. Author used HMM technique to recognized Javanese character by using vertical and horizontal feature extraction and found the result approximately 85.7% [15]. The author devolved a method for online Arabic handwriting recognition using HMM by taking the feature nearby edge, super fragment and circle with accuracy 89.75% [16]. The author designed a model to recognize numeral using HMM with the help of feature like statistical feature, structural and global transformation and moments along with the feature like end points, junction points and found the accuracy up to 84.5% [17]. Bangla character can be recognizing by using HMM and Dirichlet distribution using the stroke feature and the author found the accuracy 91.85% [18]. Author have devolved a method for cursive Arabic Handwriting recognition based on HMM having feature extraction different level of line and zone and found e accuracy up to 87.93% [19]. Symbol Tree and HMM based system for recognizing Hindi writing was purposed by author taking the feature upper region, middle region, lower region, Matra, baseline and implement the feature using gradient and HOG and the accuracy of this method relies on number of containers bins of hog and states [20]. An efficient Odia numerals recognition was reported by taking linear discriminant analysis with reduced feature from the output of PCA and found accuracy up to 96.7% [21]. Character can be recognized by using the method HMM by taking the feature bounding box and character should have the same height and found the accuracy up to 98% [22].

III. PREPROCESSING

The OCR system consists of a various phases as inputting the image, binarization of the input image, removal of noise, thinning and thickening, segmentation, skew detection and correction, feature detection and extraction and finally the classification.

A. Input image

A scanned Image or printed image can be used as the input image.





Fig. 5. Input Image for Preprocessing

**B. Binarization**

A picture is the arrangement of pixel. Binarization is the procedure which changes over this pixel picture into parallel picture. It changes over 256 dimension pictures into a highly contrasting picture. It is utilized as a pre-processor before OCR. Picture binarization used to pick a limit respect and coordinate all pixels with qualities over this edges as white and every single other pixel as dark.

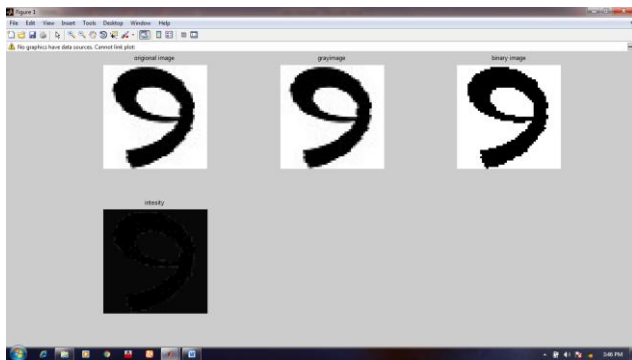


Fig. 6. Binarized Image

**C. Normalization**

In picture handling, Normalization is utilized to change the scope of pixel force esteems. It is likewise called as complexity extending or histogram extending. In the field of information preparing, for example, computerized picture handling it is alluded to as unique range extension. In preprocessing standardization assumes a significant job, it incorporates different methods, for example, scaling, interpretation, revolution.

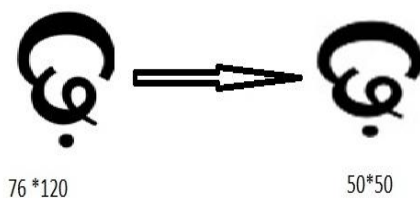


Fig. 7. Image after Normalization

**D. Noise**

Noise is brightness or shading data in image. This noise can be delivered by the sensor or advanced camera. To remove or decrease the noise from the image Noise Removal algorithm is utilized. This algorithm is utilized to remove noise present

in the picture by smoothing the entire picture leaving areas close contrast limits.

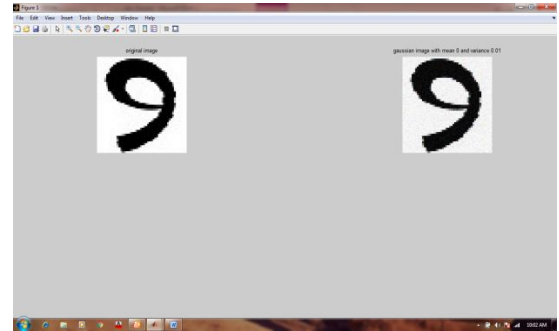


Fig. 8. Image after Removal of Noise

**E. Segmentation**

The process used to divide the image into multiple segments is defined as segmentation. By using segmentation one can disentangle and change the portrayal of a picture that is increasingly significant and simpler to investigate. There are three type of segmentation such as Segmentation detecting line, Segmentation detecting word, Segmentation detecting character.

Here bounding box is used to represent the segmentation method. In computerized picture handling, the bounding box is only the directions of the rectangular outskirts that completely encase an advanced picture when it is put over a page.

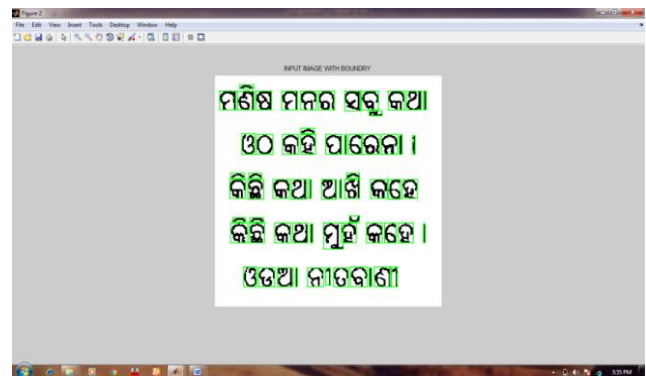
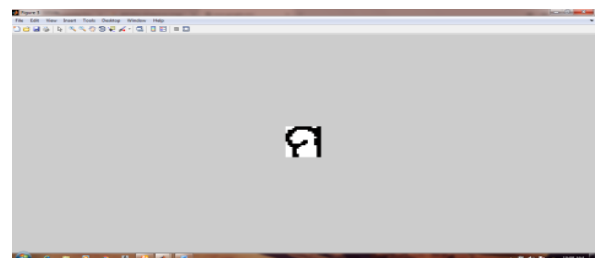
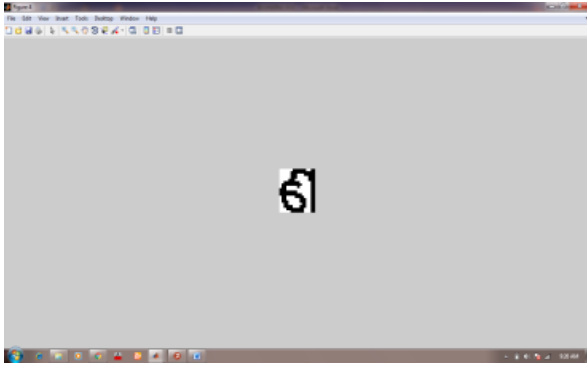


Fig. 9. Image Word Segmentation

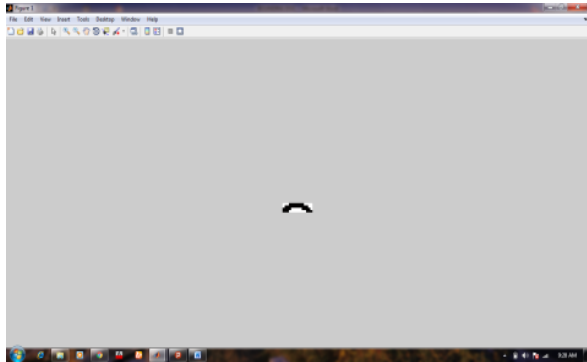
Character division is the procedure to separate a picture of a gathering of character into single character.



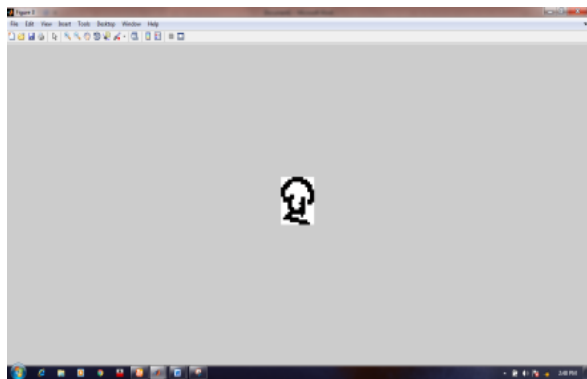
(a)



(b)



(c)



(d)

Fig. 10. Output of Individual Character after Segmentation

IV. HIDDEN MARKOV MODEL

HMM model is statistical model with unobserved state or hidden state. Mainly HMM used in speech, character recognition. After success in the speech recognition, many Researchers apply HMM for character recognition. The advantage of HMMs in cursive or composed by hand message affirmation is to perceive associated characters without fragmenting them into littler units. In less complex in this models the state is straightly visible to the observer, in this manner the only parameters are the state change probabilities, while in the HMM, the state isn't straightly see, but on the state the output reliant, is noticeable. The Hidden Markov Model comprises of a lot of limited arrangement of states which associated with one another by utilizing change likelihood. HMM can be categorized depending upon the

density function. HMM is called discrete if the observation is discrete by using quantization or vector quantization and HMM is called continuous if the observation is continuous. Hidden Markov Model can demonstrate complex Markov forms where the states produce the perceptions as per some likelihood circulation. One such example is the Gaussian distribution; in such a Hidden Markov Model the states yield are spoken to by a Gaussian circulation. In addition, it could speak to significantly increasingly complex conduct when the yield of the states is spoken to as blend of at least two Gaussians, in which case the likelihood of creating a perception is the result of the likelihood of first choosing one of the Gaussians and the likelihood of producing that perception from that Gaussian.

A. Mathematical Derivation of HMM

Hidden Markov Model can be generated from several basic parameters as

Len = observed sequence length

T = Total states number in the model

The states are  $S = \{s_1, s_2, \dots, s_T\}$

M = Total collection of observation symbols.

To represent the system's output, using the observation symbol we have to follow as:

Let the individual symbols  $U = \{u_1, u_2, \dots, u_M\}$

Q = Distinct states of the Markov process

=  $\{q_0, q_1, q_2, \dots, q_{T-1}\}$

U= Observations set  $\{0, 1, 2, \dots, M\}$

X= Transition Probability of States

The Transition probability matrix for states,  $P = \{P_{mn}\}$

Where  $P_{mn} = P(X_{n+1} = s_n | X_n = s_m), 1 \leq m, n \leq T$  (1)

Y= Probability matrix form of observation.

In state  $s_n$  the probability distribution of observation symbol can be given by  $Y = \{b_n(k)\}$  where

$b_n(k) = p(X_{n+1} = U_k | X_n = s_n), 1 \leq n \leq T, 1 \leq k \leq M$  (2)

$\Pi$  = Starting state distribution. We can represent the starting state distribution,  $\pi = \{\pi_m\}$ ,

where  $\pi_m = P\{X\} = P\{X_0 = s_m\}, 1 \leq m \leq T$  (3)

O = Sequence for Observation =  $\{o_0, o_1, o_2, \dots, o_{Len-1}\}$

We know that  $P_{mn} = P(X_{n+1} = s_n | X_n = s_m)$  (4)

We can define a Hidden Markov Model by  $\lambda = (X, Y, \pi)$

B. Forward – Backward Procedure

The issue is to compute observation probability arrangement for model with  $\lambda$ . It is conceivable to perform in a direct manner, yet this leads to a computationally in tractable solution, notwithstanding for little estimation of T. We can use the Forward-Backward algorithm for the efficient computation.

Forward variable can be define as  $\alpha_n(i)$

Where  $\alpha_n(i) = P(X_1, X_2, X_3, \dots, X_n, Z_n = s_n | \lambda)$  (5)

Where  $x_1, x_2, x_3, \dots, x_n$ : Partial observation sequence for time  $n$  with state  $s_n$  for given  $\lambda$ .

For  $n = 0$ ,



$$\alpha_0(m) = \pi_m b_m(X_0), \quad 1 \leq m \leq T \quad (6)$$

Induction leads to

$$\alpha_{n+1}(n) = \left[ \sum_{m=1}^T \alpha_n(m) p_{nm} \right] b_n(X_{n+1})$$

$$1 \leq m \leq T, \quad 1 \leq n \leq T-1 \quad (7)$$

Since  $\alpha_T(m) = P(X_1, X_2, \dots, X_T, Z_T = s_m | \lambda)$ .

It follows that

$$P(X | \lambda) = \sum_{m=1}^T \alpha_T(m) \quad (8)$$

### C. Viterbi Algorithm

This optimality basis boosts the normal number of right individual states, however it doesn't think about whether the arrangement of states is possible. The most broadly utilized basis is rather to locate the absolute best state succession, i.e. to maximize  $P(W/X, \lambda)$ . A calculation for taking care of this issue has been found and is known as the Viterbi calculation. This calculation can just be viewed as the most extreme probability gauge. We can summarize the algorithm as:

For finding the best state grouping,  $Z = \{z_0, z_1, z_2, \dots, z_T\}$  with given observation

$X = \{X_0, X_1, X_2, \dots, X_T\}$  We can compute the quantity

$$\delta_n(s_m) = \arg \max P(z_0, z_1, z_2, \dots, z_n = s_m, X_0, X_1, X_2, \dots, X_n | \lambda) \quad (9)$$

That is  $\delta_n(s_m)$  defined by best result at time n in single way at state.

$$\text{Then } \delta_{n+1}(s_n) = [\max \delta_n(s_m)] \cdot b_n(X_{n+1}) \quad (10)$$

To find the sequence for state, we have to compute the parameter that can maximize the aforesaid equation. We can solve the given problem with the help of  $\psi_n(s_j)$ . The algorithm consists of several steps as follows:

#### Initialization step:

$$\delta_0(s_m) = \pi_m b_m(X_0), \quad 1 \leq m \leq T \quad \text{and} \quad \psi_0(s_0) = 0$$

#### Repetition Step:

$$\delta_n(s_n) = [\max \delta_{n-1}(s_m) p_{nm}] b_n(X_n), \quad 1 \leq n \leq T, \quad 1 \leq m \leq T \quad (11)$$

$$\psi_n(s_n) = \arg \max [\delta_{n-1}(s_m) p_{nm}] \quad 1 \leq n \leq T, \quad 1 \leq m \leq T \quad (12)$$

#### Terminate Step:

$$p^* = \max [\delta_T(s_m)], \quad 1 \leq m \leq T \quad (13)$$

$$z_T^* = \arg \max [\delta_T(s_m)], \quad 1 \leq m \leq T \quad (14)$$

State sequence backtracking:

$$w_n^* = \psi_{n+1}(w_{n+1}^*), \quad n = T-1, T-2, \dots, 1, 0 \quad (15)$$

Using Viterbi algorithm, we get the best sequence as

$$p^* = (w_0^*, w_1^*, \dots, w_T^*)$$

### D. Baum-Welch Algorithm

To decide a strategy to modify the parameters of the given model  $\lambda = (X, Y, \pi)$  to amplify the likelihood of the perception succession. This issue is in reality impractical to settle utilizing a limited perception arrangement as preparing information, yet we can pick  $\lambda = (X, Y, \pi)$  with the end

goal that  $P(X|\lambda)$  is privately expanded utilizing an iterative methodology, for example, Baum-Welch technique. The backward variable  $\beta_n(i)$  can be defined by

$$\beta_n(m) = P(X_{n+1}, X_{n+2}, X_{n+3}, \dots, X_T | s_m, \lambda) \quad (16)$$

Where  $\beta_n(m)$  : is the partial sequence for observation probability at state  $s_m$ , with time n and model  $\lambda$ .

And induction leads to

$$\beta_n(m) = \sum_{k=0}^n p_{mk} b_j(X_{n+1}) \beta_{n+1}(n)$$

Where  $n = T-1, T-2, \dots, 1, 0, 1 \leq m \leq T$  (17)

Given  $\xi_n(m, n)$  : probability for state  $s_m$  at time n and state  $s_n$  at time  $n+1$

$$\xi_n(m, n) = P(w_n = s_m, w_{n+1} = s_n | X, \lambda) \quad (18)$$

Then by taking the help of both Forward and Backward variable we can rewrite  $\xi(m, n)$  as

$$\xi_n(m, n) = \alpha_n(m) p_{mn} b_n(X_{n+1}) \beta_{n+1}(n) \quad (19)$$

$$P(X | \lambda) = \sum_{n=1}^T \alpha_n(m) p_{nm} b_n(X_{n+1}) \beta_{n+1}(n)$$

Where  $P(w_n = s_m, w_{n+1} = s_n | X, \lambda)$  we also need  $P(X | \lambda)$  : Probability measure

$Y_n(m)$  : Probability for present in state  $s_m$ , at time n.

$$y_n(m) = \sum_{n=1}^T \xi_n(m, n) \quad (20)$$

To re-estimate the parameter of HMM

$\pi_i$  = Predicted frequency in state  $s_m$  at time  $t=1 = y_n(m)$

$$P_{ij} = \frac{\text{Predicted number of transitions from state } s_m \text{ to state } s_n}{\text{Predicted number of transitions from state } s_m}$$

$$= \frac{\sum_{n=1}^{T-1} \xi_n(m, n)}{\sum_{n=1}^{T-1} y_n(m)} \quad (21)$$

$$b_j(k) = \frac{\text{Predicted number of time in state } s_n \text{ and observing symbol } v_k}{\text{Predicted number of time in } s_n}$$

$$= \frac{\sum_{n=1}^T y_n(n) \cdot I_{X_n=v_k}}{\sum_{n=1}^T y_n(n)}$$

## V. FEATURE EXTRACTION

### A. Moment based Features

There are several types of feature can be taken based on moment of characters as

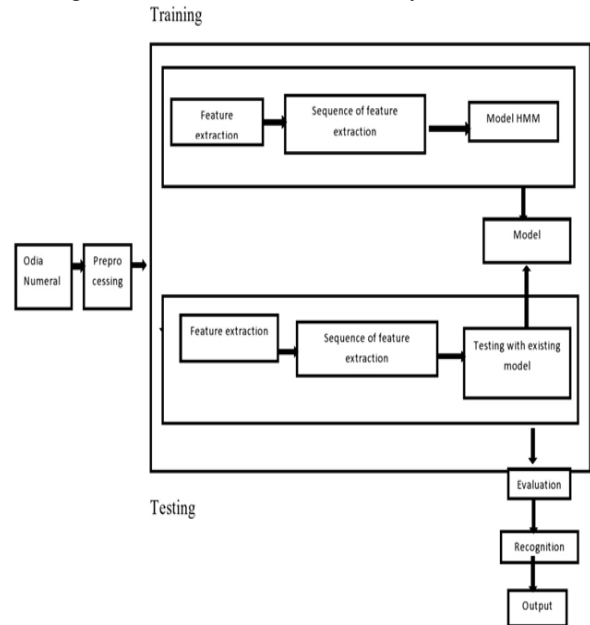
- Total number of pixel: Pixel is the most little segment of an image. Every pixel compare to any one value. In a 8-bit dark scale picture, the estimation of the pixel some place in the scope of 0 and 255.
- Center of the image or centroid: The centroid or geometric focal point of a plane figure is the number math mean position of the impressive number of centers in the figure.

- Eccentricity (Major/ Minor axis): The Eccentricity of a conic area is a non-negative genuine number that remarkably describes its shape.
- Orientation (angle formed by major axis): Orientation of edge pixels suggests their course. An edge may have a vertical Orientation or an even Orientation, or it might be inclined. You can speak to the edge Orientation by a point.
- Skewness: In picture handling, Darkened and brighter surfaces will administer in doubt be more unequivocally skewed than bright and colorless surfaces. Thus skewness can be utilized in settling on decisions about picture surfaces.
- Kurtosis: In image processing kurtosis values are translated in blend with commotion and goals estimation.
- Moment order: In digital image processing, a picture moment is a sure specific weighted normal of the picture pixels' forces, or a component of such moment, ordinarily picked to have some appealing property or understanding.
- Chain code representation: A chain code is a lossless pressure calculation for monochrome pictures. The fundamental rule of chain codes is to independently encode each associated segment, or "mass", in the picture.
- Hough Transform: The motivation behind the method is to discover defective occasions of items inside a specific class of shapes by a casting a voting system.
- Fourier Transform: The Fourier Transform is a significant picture handling instrument which is utilized to deteriorate a picture into its sine and cosine parts.
- Contour or edges of object: The term 'edge' is for the most part used to mean picture focuses where power distinctions between pixels are huge. Then again, the term contour is utilized to signify object limit.

## B. Structural Feature

- Aspect Ratio: The proportion of an image's width-to-height is known as its Aspect Ratio. A picture with a viewpoint proportion more than 1 is known as a "scene" picture. A picture with a perspective proportion under 1 is known as a "representation" picture. At the point when the viewpoint proportion is actually 1, the picture is square.
- Intersection Points: An intersection point is where two lines or lanes cross.
- Circles: A circle is a direct closed shape. It is the course of action of all concentrations in a plane that are at a given detachment from a given point.
- Branch Points: By a branch point we mean an area where a procedure bifurcates.
- Strokes: Strokes detection can be give better result using the thinning image.
- Vertical Bar: Vertical lines will be lines that go straight all over.
- Angled bar (Slant angle): A point is comprised of two beams that have a similar starting point.
- End points: The number of position in which the character finished.
- Inflection between points: Inflection is a point on a

persistent plane bend at which the bend changes from being curved to arch or the other way around.



**Fig. 11. Overall Flow Diagram of the Proposed Model**

## VI. EXPERIMENTAL RESULTS

In this purposed model, we have considered 10 numbers of numerals with different Fonts, sizes and orientations. There are 500 types of different representation of each number, resulting total 5000 number of data set are implemented. Here we have select the optimal HMM parameter based on the results generated from evaluation data. Since each font and size has its own parameter, hence the recognition becomes so difficult. The accuracy of recognition of different Odia numerals are plotted using Matlab2014a and are explained below figures with respect to time, sample set etc.

First we performed some of the preprocessing steps like binarization, normalization, skew correction and detection, segmentation on the given input data set then by using Moment based Feature and Structural Feature, we train the model on HMM. The recognition accuracy for different numerals and confusion matrix are given in table1 and table2.

**Table- I: Accuracy Result for Recognition Using Number of States**

| Numeral | Number of States in HMM | Recognition Accuracy (%) | Error Accuracy (%) |
|---------|-------------------------|--------------------------|--------------------|
| ୦       | 15                      | 100%                     | 0%                 |
| ୧       | 18                      | 98%                      | 2%                 |
| ୨       | 14                      | 97.45%                   | 2.55%              |
| ୩       | 17                      | 94.13%                   | 5.87%              |
| ୪       | 16                      | 95.45%                   | 4.55%              |
| ୫       | 12                      | 93.34%                   | 6.66%              |

|   |    |        |       |
|---|----|--------|-------|
| ୨ | 18 | 94.31% | 5.69% |
| ୩ | 15 | 93.75% | 6.25% |
| ୮ | 17 | 99.90% | 0.10% |
| ୯ | 12 | 96.73% | 3.27% |

Table- II: Confusion Matrix for the Odia Numerals

|            | ୦<br>Suna | ୧<br>Eka | ୨<br>Due | ୩<br>Teen | ୪<br>Chari | ୫<br>Panch | ୬<br>Chha | ୭<br>Sata | ୮<br>Atha | ୯<br>Naa |
|------------|-----------|----------|----------|-----------|------------|------------|-----------|-----------|-----------|----------|
| ୦<br>Suna  | 98        | 0        | 0        | 0         | 2          | 0          | 0         | 0         | 0         | 0        |
| ୧<br>Eka   | 0         | 97       | 2        | 0         | 0          | 0          | 0         | 0         | 0         | 1        |
| ୨<br>Due   | 0         | 0        | 94       | 0         | 0          | 0          | 2         | 2         | 0         | 0        |
| ୩<br>Teen  | 0         | 0        | 0        | 95        | 0          | 0          | 0         | 2         | 0         | 1        |
| ୪<br>Chari | 2         | 0        | 2        | 0         | 93         | 2          | 0         | 1         | 0         | 0        |
| ୫<br>Panch | 0         | 0        | 1        | 1         | 3          | 94         | 0         | 0         | 0         | 1        |
| ୬<br>Chha  | 0         | 0        | 3        | 0         | 0          | 0          | 95        | 2         | 0         | 0        |
| ୭<br>Sata  | 0         | 0        | 2        | 1         | 0          | 0          | 3         | 94        | 0         | 0        |
| ୮<br>Atha  | 0         | 0        | 0        | 0         | 1          | 0          | 0         | 0         | 98        | 1        |
| ୯<br>Naa   | 0         | 0        | 0        | 0         | 0          | 0          | 2         | 1         | 0         | 97       |

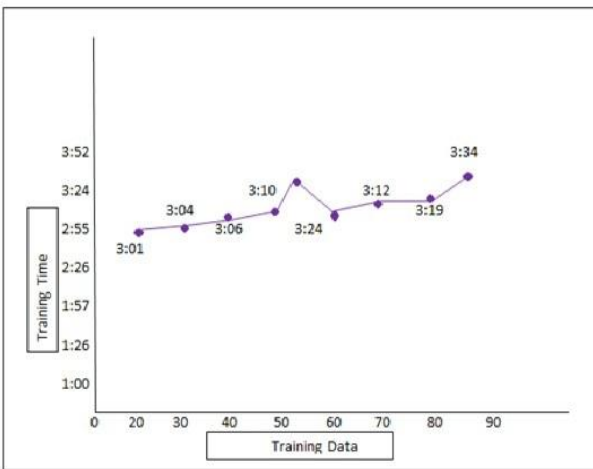


Fig. 12. Recognition Time Elapsed with Training Data

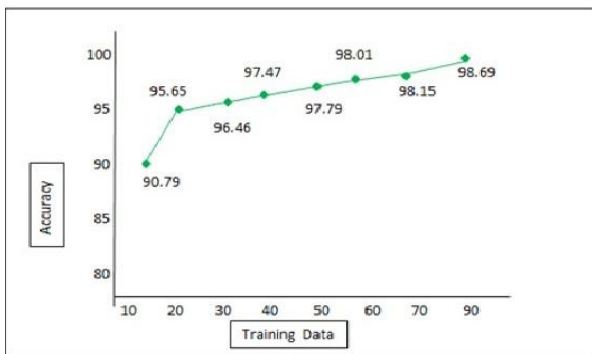


Fig. 13. Recognition Accuracy with Training Samples

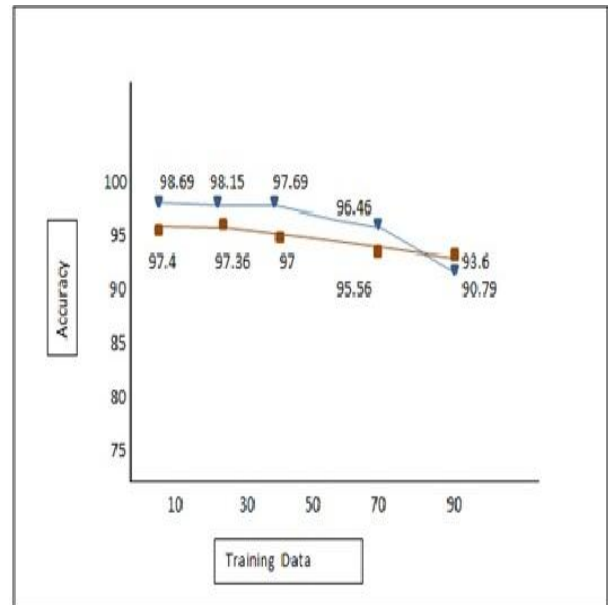


Fig. 14. Comparison of Accuracy Between Training and Testing Data

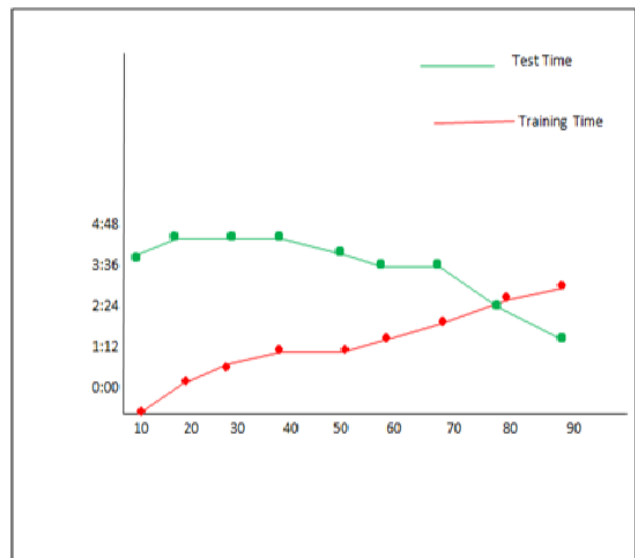


Fig. 15. Variation in Recognition Accuracy with Different Parameters

VII. CONCLUSION

In the proposed model, we have developed an OCR unit to recognize the Odia numeral based on Moment Feature and Structural Feature with implementation in HMM. We also focused on multi font representation of Odia numerals and we found that this method is more effective than other approaches with recognition rate 96.306 %. In future we have to extend our work with some more feature dimension reduction methods and to work on complex shaped, similar shaped characters.



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