"Research is creating new knowledge"

-Neil Armstrong

Chapter 6

OFFLINE HANDWRITTEN DEVANAGARI WORD RECOGNITION SYSTEM USING ADAPTIVE BOOSTING APPROACH

6.1 INTRODUCTION

Recognition of offline handwritten Devanagari words is a challenging and problematic task. Handwriting recognition can be carried out using either analytic or holistic based approach. Holistic based approaches i.e. word level recognition of Indic scripts is at its beginning phase as compared with Non-Indic scripts such as Latin, Oriental scripts etc. This chapter presents a comprehensive study of holistic based approaches for offline handwritten Devanagari word recognition based various feature and classifier combinations. In the present work, the performance of three feature extraction techniques namely zoning-based, peak extent-based and Gabor filter-based along with three classification techniques namely support vector machine, naive bayes and random forest have been analyzed for recognition of handwritten Devanagari words. To improve recognition results, adaptive boosting approach and different feature-classifier combinations have been considered.

Section 6.2 gives overview of feature extraction techniques explored for HDWR. Further, Adaptive Boosting (AdaBoost) approach is briefly discussed in Section 6.3. Section 6.4 presents experimental results along with their discussion. Comparison with the state-of-the-art work and syntactic analysis have been given in Section 6.5. Finally, Section 6.6 summarizes the entire chapter.

6.2 FEATURE EXTRACTION TECHNIQUES

Feature extraction techniques are used extract meaningful information from handwritten word images, on the basis of which one can able to distinguish one character/word from the other (Pal et al., 2009b; Singh et al., 2022a). Hence, the recognition accuracy of handwritten Devanagari word recognition system also depends upon the feature extraction techniques used (Jayadevan et al., 2011; Sachdeva and Mittal, 2022). In this work, three feature extraction techniques namely zoning-based feature extraction, peak extent-based feature extraction and Gabor filter-based feature extraction are explored to develop a handwritten Devanagari word recognition system. Moreover, various combinations of these techniques have also examined to check their suitability for handwritten Devanagari word recognition. The above said feature extraction techniques are briefly outlined in the following subsections.

6.2.1 Uniform Zoning-based Features

Each handwritten Devanagari word image is separated into n equal-sized zones using this technique. Thereafter, the foreground pixels $(f_1, f_2, f_3, , \dots \dots \dots , f_n)$ of each zone is calculated. To obtain a set of feature vectors these foreground pixels are normalized to $[0, 1]$ (Kaur and Kumar, 2021a; Kumar et al., 2018a). In this work, handwritten word images (each of size: 256×64) are divided into four equal zones (refer Fig. 6.1(b)), thereafter each zone is further divided into 16 zones (refer Fig. 6.1(c)) and finally, each zone is divided into 64 zones, resulting total 85 (1+4+16+64) zones of the image of a handwritten word that can be utilized to determine its foreground pixel density. The steps of zoning-based feature extraction (FC1) are summarized as below:

- Thinned bitmapped image of handwritten Devanagari word is inputted.
- The above image is divided into n-zones of equal size, in hierarchical way.
- Calculate, the number of black pixels (foreground pixels) in each zone.
- Calculate, pixel density of the each zone using the following expression:

$$\text{Pixel density} = \frac{\text{Number of object pixels in each region}}{\text{Total number of pixels}}$$

- Use the value of pixel density of each zone to construct a feature vector.
- Thereafter, normalize the values of the feature vector obtained as above.

- Finally, 85 features of a handwritten Devanagari word image are extracted.

Zone illustrations considering the whole word image as single zone, 1×4 zones, 2×8 zones and 4×16 zones of a handwritten word image namely “मणिपुर” (Manipur) are depicted in Fig. 6.1.

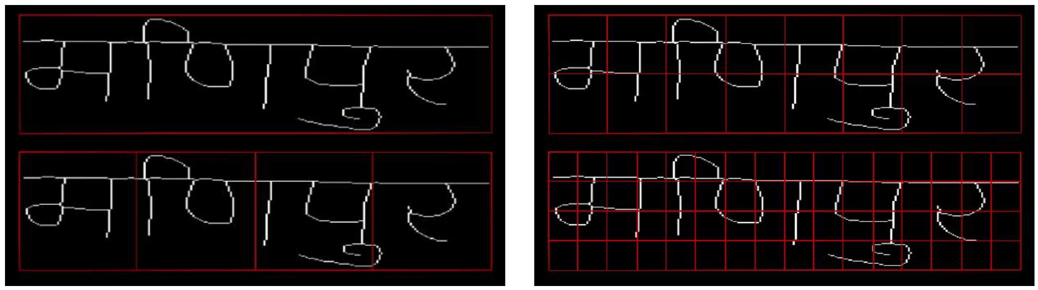
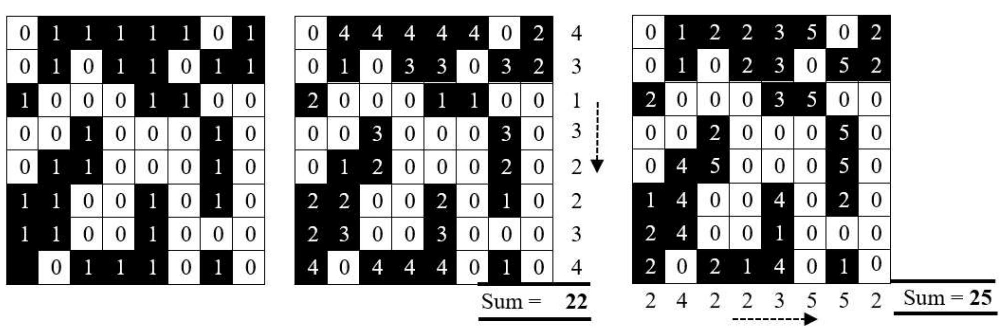


Figure 6.1: Zone illustrations considering the whole word image as **(a)** single zone, **(b)** 1×4 zones, **(c)** 2×8 zones and **(d)** 4×16 zones of a word image

6.2.2 Peak Extent-based Features

Peak extent-based features were initially proposed by (Kumar et al., 2013) to develop an offline handwritten Gurumukhi character recognition system. Thereafter, these features were explored by (Kaur and Kumar, 2021a) for the recognition handwritten Gurumukhi words. In this work, these features are extracted from handwritten Devanagari word images to develop an offline handwritten Devanagari word recognition system. These features can be extracted by considering various zones in the word images. Thereafter, extraction of features are carried out by considering the sum of the peak extents (horizontal and vertical) that fit consecutive black pixels along the every zone (refer Fig. 6.2).



(a) **(b)** **(c)**

Figure 6.2: Illustration of zoning of **(a)** bitmap word image, **(b)** horizontally and **(c)** vertically peak extent features

If the sum of the peak extents that fit consecutive black pixels, are considered horizontally then horizontal peak extent features can be extracted (refer Fig. 6.2b). Otherwise, if considered vertically then vertical peak extent features can be extracted (refer Fig. 6.2c). In this work, 170 peak extent features including 85 horizontal and 85 vertical peak extent features are extracted from the handwritten Devanagari word images.

6.2.3 Gabor Filter-based Features

Gabor filters have been widely used in image processing and pattern recognition field because of their properties of less sensitivity to noise and immunity towards a small range of rotation, transformation and scaling. Gabor filter is a linear filter, and its impulse response is defined by a harmonic function multiplied by a Gaussian function (Narang et al., 2020) as given in Eq. 6.1:

$$h(x, y) = g(x, y)s(x, y) \tag{6.1}$$

Where, $s(x, y)$ is complex sinusoid, recognized as carrier and (x, y) is a Gaussian-shaped function, recognized as an envelope.

2-D Gabor filter is given by Eq. 6.2:

$$h\left(x, y, \lambda, \phi, \sigma_x, \sigma_y\right) = \frac{1}{2\pi\sigma_x\sigma_y} exp\left\{\frac{-1}{2}\left[\frac{R_1^2}{\sigma_x^2} + \frac{R_2^2}{\sigma_y^2}\right]\right\} \times exp\left[i \cdot \frac{2\pi R_1}{\lambda}\right] \tag{6.2}$$

Where, $1 = \cos\emptyset + \sin\emptyset, 2 = -\sin\emptyset + \cos\emptyset$, $\emptyset$ is orientation and λ is the wavelength of the harmonic plane.

In the above equation, it is assumed that standard deviation $\sigma_x = \sigma_y = \sigma$. In this work, Gabor filters are calculated for each orientation. Eight orientations from $0\ to\ \pi\ \left\{0, \frac{\pi}{8}, \frac{2\pi}{8}, \frac{3\pi}{8}, \frac{4\pi}{8}, \frac{5\pi}{8}, \frac{6\pi}{8}, \frac{7\pi}{8}, \pi\right\}$ are used.

For eight orientations, eight feature sets of values have been calculated. Also, Gabor features with four frequencies $(\lambda)\left\{0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}\right\}$ are calculated. With eight orientations and four frequencies, 32 filters are gotten as depicted in Fig. 6.3.

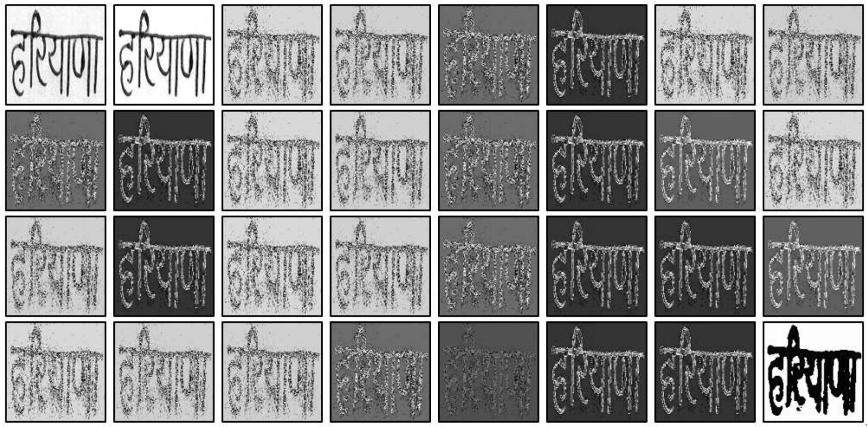


Figure 6.3: Illustration of Gabor filter with 8-orientations and 4-frequencies (32-filters)

The size of an output handwritten word image that has been convolved with a Gabor filter is consistent with the size of the input image. The retrieved features have a dimensionality of 4096 because the size of image is 64×64. As the dimensionality of the feature vector directly affects processing time and storage, therefore feature reduction has been applied using Principal Component Analysis (PCA). In this work, feature vector dimensionality has reduced from 4096 to 60 using PCA. The principle component analysis does not use class information (Narang et al., 2020). PCA is a mathematical procedure to reduce the dimensions of data based on the orthonormal transformation.

6.3 Adaptive Boosting (AdaBoost) Approach

In this work, Support Vector Machine with Radial Basis Function kernel (SVM-RBF), Naive Bayes (NB) and Random Forest (RF) classifiers are used to recognize the handwritten Devanagari words. SVM finds the hyperplane with maximum margin and reduces the generalized error. NB is suitable for multi-class prediction tasks and can handle both continuous as well as discrete data. It does not need as abundant training data. RF classifier can handle the high dimensional noisy data and suitable for text classification (Islam et al., 2019a). These classifiers are briefly outlined in the following subsections. Boosting is an ensemble based machine learning algorithm which attempts to create a stronger classifier through the ensembling of weak classifiers (Kumar et al., 2019b). Classification or recognition accuracy of individual algorithm could be improved using combination of various classifiers. Adaptive Boosting (AdaBoost) is a commonly used boosting algorithm for many applications such as speech recognition and moving vehicle classification etc. (Rahim et al., 2013). In this work, AdaBoost is explored to enhance the performance of classifiers for handwritten Devanagari word recognition. Adaptive Boosting (AdaBoost) approach was proposed by (Freund and Schapire, 1997). It could be integrated with SVM, NB and RF classifiers so as to enhance their recognition performance. In this work, AdaBoost is used to build strong classifier by boosting the performance of SVM, NB and RF classifiers. It can be accomplished through assortment of training at each replication and assigning the precise weight in the last stage (Rahim et al., 2013). The pseudo-code for the AdaBoost is given as follows:

Input: Sequence of the n-training datasets, $D = \{(x_1, y_1), (x_2, y_2), \dots \dots \dots (x_n, y_n)\}$, $x_i \in X$, with labels

$y_i \in Y = \{\gamma_1, \gamma_2, \dots\dots\dots \gamma_c,\}$, where γ_i, represents the number of classes.

{

Transform weights $w_t(i) = 1/n$; for $i = 1, 2, \dots \dots \dots n$

For $t = 1, 2, \dots \dots \dots T$; Number of learning rounds

{

Using $w_t(i)$ to train a weak classifier $g_t(x)$

Choose $g_t(x)$ with low weighted error $E_t = \sum_{i=1}^{n} w_t(i)\, I\, (y_i \neq g_t(x_i))$

Specify $\beta_t = \frac{1}{2} \ln((1 - E_t)/E_t)$

Update weight $w_{t+1} = w_t(i) exp\{-\beta_t y_i g_t(x)\}/Z_t$ for $i = 1,2, \dots \dots \dots n$

// where Z_t represent a normalization factor

}

Output: //boosted output is specified by

$G(x) = sign\left(\sum_{t=1}^{T} \beta_t\, g_t(x)\right)$

}

By reducing the training error, AdaBoost could increase the accuracy of the classifier by correctly selecting the optimally weak classifier and weighted majority voting.

6.4 EXPERIMENTAL RESULTS AND DISCUSSION

This section presents the experiment results based on a corpus of 48,000 handwritten Devanagari words. The corpus has been divided into 38,400 words as training samples (i.e. 80% of data) and whereas, 9,600 words as testing samples (i.e. 20% of data). Analytical study of Handwritten Devanagari Word Recognition (HDWR) System has carried out in terms of various performance parameters namely Recognition Accuracy

(RA), False Acceptance Rate (FAR), False Rejection Rate (FRR), F1-Score (FS) and Area Under the Curve (AUC). Parameter-wise experimental results are given in Tables 6.1 to 6.5 for various feature extraction and classification techniques considered for this work.

6.4.1 Recognition Results in terms of Recognition Accuracy (%)

Recognition accuracy (%) of HDWR system are presented in the Table 6.1. The minimum value of recognition accuracy has obtained using peak extent-based feature extraction (FC2) and SVM-RBF classification approach for a given set of handwritten word images. It has observed that recognition accuracy improves with the combination of various feature extraction techniques considered for this work. Combination of various feature extraction techniques (FC1+FC2+FC3) namely zoning-based, peak-extent-based and Gabor filter-based along with random forest classification approach gives 82.69% of recognition accuracy. Further, it has analyzed that recognition accuracy of HDWR system improves by considering adaptive boosting approach (AdaBoost). It has observed that combination of various feature extraction (FC1+FC2+FC3) and classification techniques followed by AdaBoost approach results highest recognition accuracy of 89.12% as given in Table 6.1.

Table 6.1: Recognition Accuracy (RA) (in %) of HDWR system

Feature Extraction Techniques	Classification Techniques			
	Support Vector Machine (SVM-RBF)	Naive Bayes (NB)	Random Forest (RF)	AdaBoost Approach
Zoning-based (FC1)	66.67%	66.91%	76.59%	84.87%
Peak extent-based (FC2)	64.81%	65.84%	74.40%	82.96%
Gabor filter-based (FC3)	67.90%	68.72%	78.06%	85.88%
FC1+ FC2	69.33%	71.12%	80.89%	86.73%
FC1+ FC3	69.53%	70.55%	81.65%	87.38%
FC2+ FC3	69.91%	71.45%	81.94%	87.54%
FC1+ FC2+ FC3	70.18%	72.89%	82.69%	89.12%

6.4.2 Recognition Results in terms of FAR (%)

Table 6.2, presents the False Acceptance Rate (FAR) (%) of HDWR system. It has observed that peak extent-based features extraction technique and SVM-RBF classification technique results the maximum value of FAR (%) i.e. 0.29%. The value of FAR (%) decreases when various combination of features extraction techniques considered for this work have been taken together. It has examined that combination of various feature extraction techniques viz. zoning-based, peak-extent-based and Gabor filter-based and classification techniques followed by AdaBoost approach results the minimum value of FAR (%) i.e. 0.09% as given in Table 6.2.

Table 6.2: False Acceptance Rate (FAR) (in %) of HDWR system

Feature Extraction Techniques	**Classification Techniques**			
	Support Vector Machine (SVM-RBF)	**Naive Bayes (NB)**	**Random Forest (RF)**	**AdaBoost Approach**
Zoning-based (FC1)	0.28%	0.27%	0.19%	0.12%
Peak extent-based (FC2)	0.29%	0.28%	0.21%	0.14%
Gabor filter-based (FC3)	0.26%	0.26%	0.18%	0.11%
FC1+ FC2	0.25%	0.24%	0.16%	0.11%
FC1+ FC3	0.25%	0.24%	0.15%	0.10%
FC2+ FC3	0.25%	0.23%	0.15%	0.10%
FC1+ FC2+ FC3	0.25%	0.22%	0.14%	0.09%

6.4.3 Recognition Results in terms of FRR (%)

As depicted in Table 6.3, maximum FRR (%) of 35.18% have achieved using Peak extent-based (FC2) feature extraction and SVM-RBF classification techniques.

Table 6.3: False Rejection Rate (FRR) (in %) of HDWR system

Feature Extraction Techniques	**Classification Techniques**			
	Support Vector Machine (SVM-RBF)	**Naive Bayes (NB)**	**Random Forest (RF)**	**AdaBoost Approach**
Zoning-based (FC1)	33.32%	33.08%	23.40%	15.12%
Peak extent-based (FC2)	35.18%	34.15%	25.59%	17.03%
Gabor filter-based (FC3)	32.09%	31.27%	21.93%	14.11%
FC1+ FC2	30.66%	28.87%	19.10%	13.26%
FC1+ FC3	30.46%	29.44%	18.34%	12.61%
FC2+ FC3	30.08%	28.54%	18.05%	12.45%
FC1+ FC2+ FC3	29.81%	27.10%	17.30%	10.87%

It shows that combination of various feature extraction techniques viz. zoning-based, peak-extent-based and Gabor filter-based and classification techniques followed by

AdaBoost approach results minimum FRR (%) of 10.87% for the presented HDWR system. From Table 6.3, it can also be summarized that combination of various feature extraction techniques results lower values of FRR (%) as compared with cases when only individual features extraction techniques have been considered.

6.4.4 Recognition Results in terms of F1-Score (%)

F1-Score (FS) (%) obtained from HDWR system considered for this work are presented in Table 6.4. The table indicated that minimum F1-Score of 65.24% has been obtained using Peak extent-based (FC2) feature extraction and SVM-RBF classification techniques. Maximum value of FS (%) i.e. 89.22% is obtained by using combination of various feature extraction techniques namely zoning-based, peak-extent-based and Gabor filter-based and classification techniques followed by AdaBoost approach.

Table 6.4: F1-Score (FS) (in %) of HDWR system

Feature Extraction Techniques	Classification Techniques			
	Support Vector Machine (SVM-RBF)	Naive Bayes (NB)	Random Forest (RF)	AdaBoost Approach
Zoning-based (FC1)	67.01%	67.25%	76.85%	85.05%
Peak extent-based (FC2)	65.24%	66.20%	74.68%	83.13%
Gabor filter-based (FC3)	68.24%	69.05%	78.29%	86.03%
FC1+ FC2	69.63%	71.45%	81.06%	86.87%
FC1+ FC3	69.83%	70.86%	81.82%	87.53%
FC2+ FC3	70.22%	71.77%	82.11%	87.68%
FC1+ FC2+ FC3	70.49%	73.20%	82.87%	89.22%

6.4.5 Recognition Results in terms of AUC (%)

As given in Table 6.5, maximum AUC (%) of 94.51% have obtained using combination of various feature extraction techniques viz. zoning-based, peak-extent-based and Gabor filter-based and classification techniques followed by AdaBoost approach. It shows that the lowest AUC (%) of 82.25% has obtained when considering peak extent-based (FC2) feature extraction and SVM-RBF classification techniques for the presented HDWR system. From Table 6.5, it can also be summarized that combination of various feature extraction techniques (FC1+FC2+FC3) results higher values of AUC

(%) as compared with cases when only individual feature extraction techniques have been considered.

Table 6.5: Area Under the Curve (AUC) (in %) of HDWR system

Feature Extraction Techniques	Classification Techniques			
	Support Vector Machine (SVM-RBF)	Naive Bayes (NB)	Random Forest (RF)	AdaBoost Approach
Zoning-based (FC1)	83.19%	83.31%	88.19%	92.37%
Peak extent-based (FC2)	82.25%	82.77%	87.09%	91.41%
Gabor filter-based (FC3)	83.81%	84.23%	88.93%	92.88%
FC1+ FC2	84.53%	85.44%	90.36%	93.31%
FC1+ FC3	84.63%	85.15%	90.75%	93.63%
FC2+ FC3	84.83%	85.60%	90.89%	93.71%
FC1+ FC2+ FC3	84.96%	86.33%	91.27%	94.51%

Syntactic Analysis of the proposed HDWR system has presented in the following section.

6.5 COMPARISON WITH THE STATE-OF-THE-ART WORK AND SYNTACTIC ANALYSIS

The proposed handwritten word recognition system has obtained good recognition results for many of word classes except a few. Analysis of recognition accuracy achieved using Adaboost methodology and combination of various feature extraction techniques (FC1+FC2+FC3) are presented in Fig. 6.4.

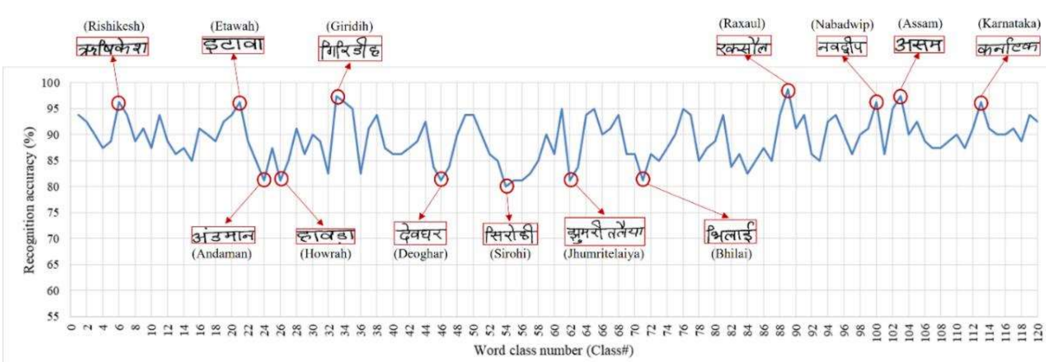


Figure 6.4: Analysis of recognition accuracy using Adaboost approach for 120-word classes considering combination of various features

It can be analyzed that recognition accuracy for 120-word classes (that are considered in this work) lies from 80% to 98.75% (using Adaboost). It has gathered that the variation in recognition accuracies among classes are due to many reasons. The reasons may include disparity in spelling in database, complex shape of words, presence of skew variation (refer Fig. 6.5), similar shaped words among various classes (confusing word classes), variation in Matra shape and overwriting in character etc. These mentioned reasons results misclassification and hence, there is a variation in class wise recognition accuracies.

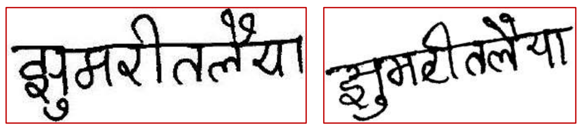


Figure 6.5: Example of skew variation

Further, analysis has been carried out in terms of the number of handwritten word-classes (in %) with recognition accuracy (using Adaboost approach) within a specified range. Experimental results indicates that 13.33% of word-classes have obtained less than 85% of recognition accuracy, 38.33% of word-classes have obtained recognition accuracy lies in the rage of 85% to 90%, 37.50% of word-classes have achieved recognition accuracy lies in the rage of 90% to 95% and few word-classes i.e. 10.84% have obtained recognition accuracy of more than 95%. Fig. 6.6 depicts the number of word-classes (in %) with recognition accuracy within a specified range using Adaboost approach.

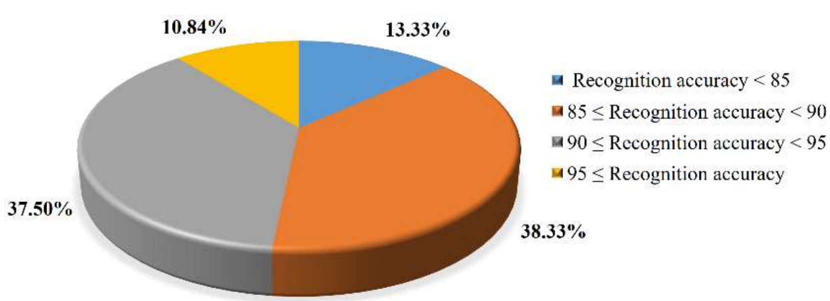


Figure 6.6: Number of word-classes (in %) with recognition accuracy within a specified range

Further, in this section, a comparative study of proposed work is carried out with the state-of-the-art work exiting in the literature. Although, due to non-availability of standard database of handwritten words, it is very hard to compare the performance of various methods/techniques. However, the comparison has been carried out in terms of recognition accuracy (%) obtained using various feature extraction and classification techniques for Devanagari, Bangla and Gurumukhi scripts. The present work has been compared with (Parui and Shaw, 2007; Shaw et al., 2008a, 2008b; Shaw and Parui, 2010; Singh et al., 2011; Shaw et al., 2014; Shaw et al., 2015; Kumar, 2016) developed for Devanagari scripts.

The work reported in (Ramachandrula et al., 2012; Malakar et al., 2017) have dealt with Hindi words. Whereas, (Bhunia et al., 2018) worked for Devanagari, Bangla and Gurumukhi scripts. The work presented in (Ghosh et al., 2019; Malakar et al., 2020a) have dealt with recognition of handwritten Bangla words, whereas the work reported in (Kaur and Kumar, 2021a, 2021b; Sharma et al., 2022) conducted study on handwritten Gurumukhi words. Comparison of proposed work with existing techniques has been summarized in the Table 6.6. From table, it can be seen that present work performs comparable and better as compared with state-of-the-art work developed so far.

Table 6.6: Comparison of proposed work with existing techniques

Authors	Script or Language	Dataset (Words)	Approach		Recognition Accuracy (%)
			Feature Extraction	**Classification**	
Parui and Shaw, (2007)	Devanagri	10,000	Stroke-based	HMM	87.71%
Shaw et al., (2008a)	Devanagri	39,700	Directional Chain Code-based	HMM	80.20%
Shaw et al., (2008b)	Devanagri	39,700	Stroke- based	HMM	84.31%
Shaw and Parui, (2010)	Devanagri	13,000	Stroke-based *(Stage-1);* Wavelet-based *(Stage-2)*	HMM *(Stage-1);* Modified Byes *(Stage-2)*	91.25% *(Stage-2)*
Singh et al., (2011)	Devanagri	28,500	Curvelet Transform-based	SVM and KNN	85.60% *(SVM);* 93.21% *(KNN)*
Ramachandrula et al., (2012)	Hindi	39,600	Directional Element-based	Dynamic Programming	79.94% *(30 Vocabulary Words);* 91.23% *(10 Vacbulary Words)*

Shaw et al., (2014)	Devanagri	39,700	Combination of Skeleton and Contour-based	SVM	79.01%
Shaw et al., (2015)	Devanagri	39,700	DDD and GSC-based	Multiclass SVM	88.75%
Kumar, (2016)	Devanagari	More than 3,500	Chain Codes, Cumulative Histograms, Gradient, Neighbor Pixel Weight-based	MLP	80.80% *(for Two Character Words)* 72.00% *(for Six Character Words)*
Malakar et al., (2017)	Hindi	4,620	Low Level-based	MLP	96.82%
Bhunia et al., (2018)	Bangla, Devanagari and Gurumukhi	3,856; 3,589 and 3,142	PHOG-based	HMM *(for Middle-Zone)* SVM *(for Upper/Lower Zone)*	Above 60.00%
Ghosh et al., (2019)	Bangla	7,500	Gradient and Modified SCF; MA-based Wrapper Filter Selection	MLP	93.00%
Malakar et al., (2020a)	Bangla	12,000	Gradient and Elliptical-based	MLP	95.30%
Kaur and Kumar, (2021a)	Gurumukhi	40,000	(a) Zoning-based (b) Diagonal-based (c) Intersection & Open-End Points-based (d) Peak Extent-based	XGBoost	(a) 91.66% (b) 91.30% (c) 88.37% (d) 86.27%
Kaur and Kumar, (2021b)	Gurumukhi	1,00,000	Zoning, Diagonal and Intersection & Open-End Point-based	KNN, RBF-SVM, Random Forest, Majority Voting, AdaBoost	88.78% *(AdaBoost)*
Sharma et al., (2022)	Gurumukhi	4,000	Convolutional Neural Network	(a) Adam Optimizer (b) SGD Optimizer	(a) 99.13% (b) 94.18%
Proposed Work	Devanagari	48,000	Zoning, Peak Extent, and Gabor Filter-based	SVM-RBF, NB, RF and AdaBoost Approach	89.12% *(AdaBoost)*

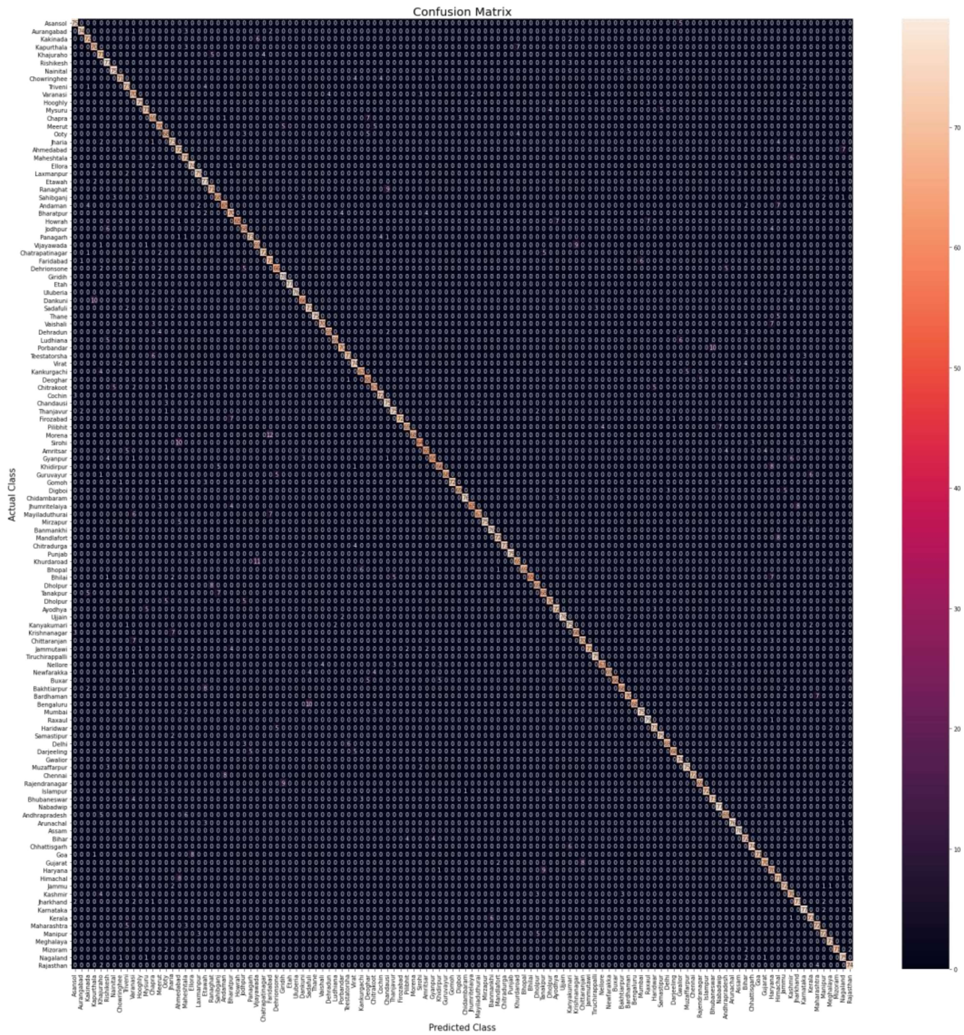


Figure 6.7: Confusion matrix

6.6 CHAPTER SUMMARY

In this chapter, a system for the recognition of handwritten Devanagari words has developed using holistic approach. In holistic approach, handwritten word image is assumed as a single and indivisible entity for recognition point of view. For this approach, three feature extraction techniques namely uniform zoning-based, peak extent-based and Gabor filter-based along with three classification techniques namely Support Vector Machine (SVM), Naive Bayes (NB) and Random Forest (RF) have considered for the recognition of handwritten Devanagari words. To improve recognition results, adaptive boosting approach and different feature-classifier combinations have been explored. On a collected corpus of 48,000 handwritten Devanagari words, it has observed that maximum recognition accuracy of 89.12%, false acceptance rate of 0.09%, false rejection rate of 10.87%, F1-Score of 89.22% and area under the curve of 94.51% have been achieved using combination of various features followed with adaptive boosting approach. After experimentation, it has concluded that combination of uniform zoning-based, peak extent-based and Gabor filter-based features followed by AdaBoost results maximum recognition accuracy for the test database. Additionally, a comparative study of proposed work is carried out with the state-of-the-art work exiting in the literature and summarized in Table 6.6. It shows that the presented system gives comparable performance with prevailing systems developed for the recognition of handwritten words.