"Excellence is a continuous process and not an accident"

-Dr. APJ Abdul Kalam

Chapter 5

RECOGNITION SCHEME FOR OFFLINE HANDWRITTEN DEVANAGARI WORDS BASED ON MAJORITY VOTING METHODOLOGY

5.1 INTRODUCTION

Development of Devanagari handwritten word recognition system is indubitably a demanding and challenging assignment for research community working in the area of pattern recognition. This challenge encourages and motivates the researchers to work for the development of many applications such as recognition of city names/pin-codes for postal automation, forensic document analysis, reading aid for blind/visually impaired users, signature/writer verification etc. Devanagari script is widely adopted in India along with other countries for writing a few languages including Hindi. So far, few attempts have been carried out for its recognition in holistic way. This chapter presents the analytical study of different combination of features and classifiers in holistic manner so as to recognize handwritten Devanagari words.

The performance of handwritten Devanagari word recognition framework has been presented in terms of various performance metrics using the in-house corpus of 48,000 Devanagari words. From the experiments, recognition accuracy of 88.06%, false acceptance rate of 0.10%, false rejection rate of 11.93%, precision of 88.83%, F1-Score of 88.20%, Matthew's correlation coefficient of 0.882 and area under the curve of 93.98% have been obtained using combination of intersection & open-end points features, elliptical features and Arnold transform based features along with majority voting classifier. Moreover, the experimental results are compared with some of the available state-of-the-art techniques. It has been gathered that the presented system achieved better or comparable performance with existing systems developed so far for the recognition of offline handwritten words.

Section 5.2 provides a detailed explanation of the different feature extraction techniques investigated in this chapter. Section 5.3 outlines the operation and methodology of the majority voting classifier. The experimental results and discussions based on various performance parameters are presented in Section 5.4. In Section 5.5, a comparative analysis between the current work and state-of-the-art approaches is presented. Finally, Section 5.6 offers a comprehensive summary of the entire chapter.

5.2 FEATURE EXTRACTION TECHNIQUES

Feature extraction plays primary role in handwritten word recognition system. This is due to the fact that the performance of these systems are determined on the basis of extracted features. So, feature extraction is very important step while developing a handwritten word recognition system. In this chapter, three features namely Intersection & open-end point based features (FB1), Elliptical-based features (FB2) and Arnold transform based features (FB3) are explored for recognition of handwritten Devanagari words. Thereafter, various classifiers are used for recognition purposes along with combination of above mentioned features. The features extraction techniques are briefly outlined in the following subsections.

5.2.1 Intersection & Open-End Point-based Features

Extraction of intersection (or junction) & open end point based features is carried out on the basis of the intersection & open end points present in each zone (Arora et al., 2008; Kumar et al., 2011) of the word images. Intersection (or junction) point refers the pixel point where, there are more than two number of neighboring pixels in eight-connectivity where as an open end point refers the pixel which has exactly one-neighboring pixel. For this, firstly input word images (uniform size of 256×64 pixels wide) are binarized using Otsu's thresholding method (Otsu, 1979) to reduce computational complexities and thereafter, thinning of these word images are carried out using (Zhang and Suen, 1984) algorithm so as to obtain unit-pixel wide skeleton of word images (refer Fig. 5.1).

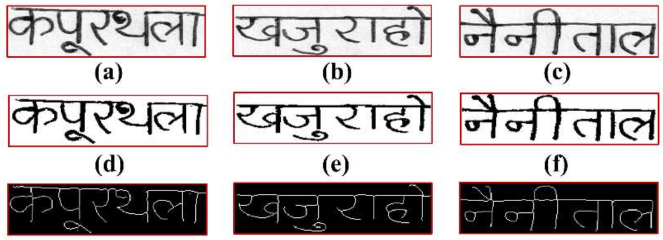


Figure 5.1: Input handwritten words **(a) to (c)**, after applying binarization **(d) to (f)** and thinning **(g) to (i)**

After that, to calculate the feature vector, the word images are partitioned into various zones and then, accordingly calculations are made for each zone (Kaur and Kumar, 2021a). For this experimental work, each word images are partitioned into 64 zones ($n = 64$) and size of each zone is 16×16 pixels wide, as given in Fig. 5.2.

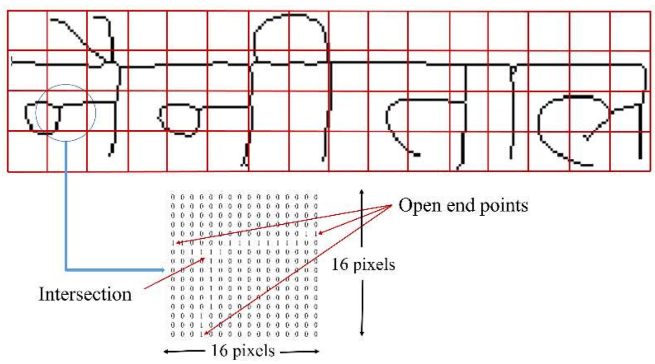


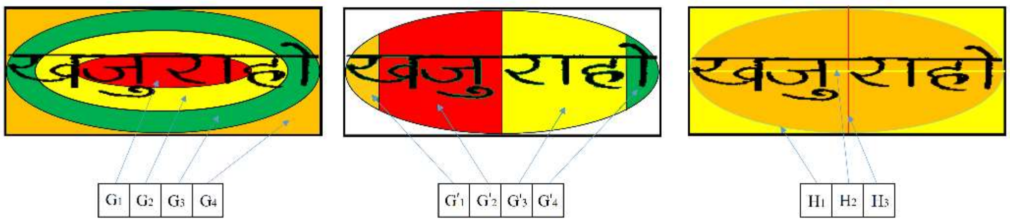
Figure 5.2: Intersection & open end point feature extraction

In this experiment, 64 intersection features and 64 open end point based features are extracted and obtained the feature vector with 128 (= 64 + 64) features.

5.2.2 Elliptical-based Features

Elliptical features are shape-dependent structural features that can be used to extract local and global features from handwritten word images. For this experimental work, firstly scanned input word images $h(x, y)$ are binarized using Otsu's method (Otsu, 1979) and thereafter, median filtering is carried out to minimize the noise in images. After noise removal, the resultant images are represented by say $m(x, y)$. Where, $m(x, y)$= "1" signify the object and $m(x, y)$= "0" indicates the background pixels of the image, respectively. After that, three concentric ellipses are abstracted over handwritten word images as depicted in Fig. 5.3(a). It results four regions namely

G_1 (red color), G_2 (yellow color), G_3 (green color) and G_4 (orange color). Apart from that, three elliptical contours acts as separating lines (orange-green, green-yellow and yellow-red) for mentioned four regions. Further, these four regions are partitioned into G'_1 (orange color), G'_2 (red color), G'_3 (yellow color) and G'_4 (green color) regions on the basis of three parallel lines at minor axis as given in Fig. 5.3 (b). One line is positioned in the center of minor axis and other two are at foci-points of the ellipse.



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

Figure 5.3: Example of various local regions along with contours, major and minor axes of ellipse taken for calculating the elliptical features for a Devanagari word image "खजुराहो" (Khajuraho)

Thereafter, various global elliptical features are extracted as mentioned in (Malakar et al., 2020) for Devanagari words. Finally, local features are extracted by dividing word images into four sub-parts along both the axes (major and minor) of outermost ellipse as represented in Fig. 5.3 (c), where, H_1, H_2 and H_3 denote the contour, major axis and minor axis of the assumed ellipse (outermost). The following equations (Eqs. 5.1 to 5.13) are used to extract above mentioned features ($\Psi_i, i = 1,2, \ldots .13$) as described in (Bhowmik et al., 2014a; Malakar et al., 2020a):

$$\Psi_1 = |\{(x,y):(x,y) \in G_1\} \wedge (m(x,y) = '1')| \quad (5.1)$$

$$\Psi_2 = |\{(x,y):(x,y) \in G_2\} \wedge (m(x,y) =' 1')| \quad (5.2)$$

$$\Psi_3 = |\{(x,y):(x,y) \in G_3\} \wedge (m(x,y) = '1')| \quad (5.3)$$

$$\Psi_4 = |\{(x,y):(x,y) \in G_4\} \wedge (m(x,y) = '1')| \quad (5.4)$$

$$\Psi_5 = \frac{|\{(x,y):(x,y) \in (G_1 \cup G_2 \cup G_3) \wedge (m(x,y) = '1')\}|}{|\{(x,y):(x,y) \in G_4\} \wedge (m(x,y) = '1')|} \quad (5.5)$$

$$\Psi_6 = \frac{|\{(x,y):(x,y) \in (G_1 \cup G_2 \cup G_3) \wedge (m(x,y) = '1')\}|}{|\{(x,y):(x,y) \in (G_1 \cup G_2 \cup G_3) \wedge (m(x,y) = '0')\}|} \quad (5.6)$$

$$\Psi_7 = |\{(x,y):(x,y) \in G'_1\} \wedge (m(x,y) = '1')| \quad (5.7)$$

$$\Psi_8 = |\{(x,y):(x,y) \in G'_2\} \wedge (m(x,y) = '1')| \quad (5.8)$$

$$\Psi_9 = |\{(x,y):(x,y) \in G'_3\} \wedge (m(x,y) = '1')| \quad (5.9)$$

$$\Psi_{10} = |\{(x,y):(x,y) \in G'_4\} \wedge (m(x,y) = '1')| \quad (5.10)$$

$$\Psi_{11} = |\{(x,y):(x,y) \in H_1\} \wedge (m(x,y) = '1')| \quad (5.11)$$

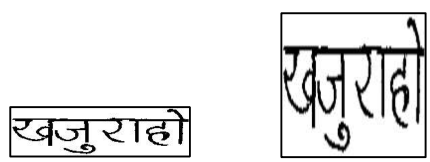
$$\Psi_{12} = |\{(x,y):(x,y) \in H_2\} \wedge (m(x,y) = '1')| \quad (5.12)$$

$$\Psi_{13} = |\{(x,y):(x,y) \in H_3\} \wedge (m(x,y) = '1')| \quad (5.13)$$

Eqs. 5.1 to 5.6 belong to four regions namely G_1, G_2, G_3 and G_4. Whereas, Eqs. 5.7 to 5.10 are concerned with another four regions namely G'_1, G'_2, G'_3 and G'_4. Last three equations (i.e. Eqs. 5.11 to 5.13), signify contour, major axis and minor axis, respectively (namely H_1, H_2, and H_3).

5.2.3 Arnold Transform-based Features

Arnold transform has been explored for the extraction of handcrafted directional features (Dasgupta et al., 2016; Gupta et al., 2018) from handwritten word images. For this, entire corpus of handwritten word images are required to be resized as square images so that period of transform can be calculated conveniently, as depicted in Fig. 5.4. Further, it helps to construct directional based feature vector on the basis of the same.



(a) **(b)**

Figure 5.4: Example of handwritten Devanagari word "खजुराहो" (Khajuraho) **(a)** before and **(b)** after resizing into square

In this work, Arnold transform based features are extracted from handwritten Devanagari words similar to that as carried in (Dasgupta et al., 2016; Gupta et al., 2018) for various databases of handwritten words. Parameters considered for extracting Arnold transform based features are as follows: $S = 144, L = 3, T = 12, \Delta\emptyset = 15^0, w = 12$ and $f = \sum_{j=0}^{2} 4^j \times 12 \times 12$. Where, S represents image size, L denotes number of levels, T denotes period of Arnold transform, $\Delta\emptyset$ signifies step size of angle, w denotes sliding window width and f represents the number of globally oriented features. Fig. 5.5 shows some illustrations of Arnold transformed images of handwritten Devanagari word "खजुराहो" (Khajuraho).

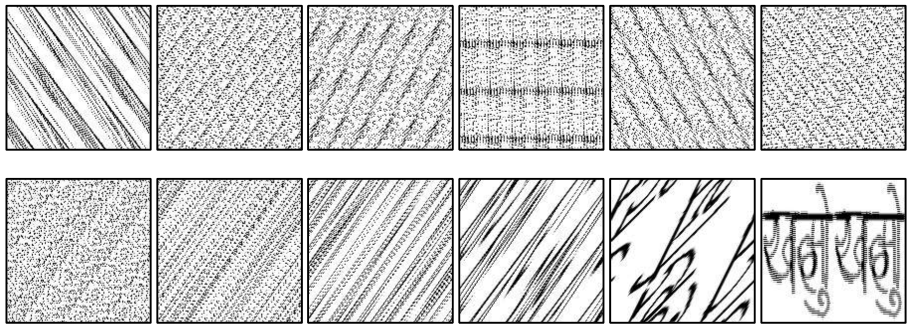


Figure 5.5: Some illustrations of Arnold transformed images of handwritten Devanagari word “खजुराहो” (Khajuraho)

5.3 MAJORITY VOTING METHODOLOGY

Classification is considered as decision taking step of an offline handwritten Devanagari word recognition system. For deciding the class of handwritten words, this step takes the information from feature vectors which were constructed in the previous step. The majority voting classifier is a technique used in handwritten word recognition for combining the predictions of multiple individual classifiers. It operates based on the principle that aggregating the decisions of multiple classifiers can lead to improved accuracy and robustness in the recognition task. In the Majority Voting classifier, each individual classifier independently assigns a label or prediction to a given handwritten word image. The final prediction is determined by selecting the label that receives the majority of votes from the individual classifiers. Majority voting classifier is shown in the Fig. 5.6.

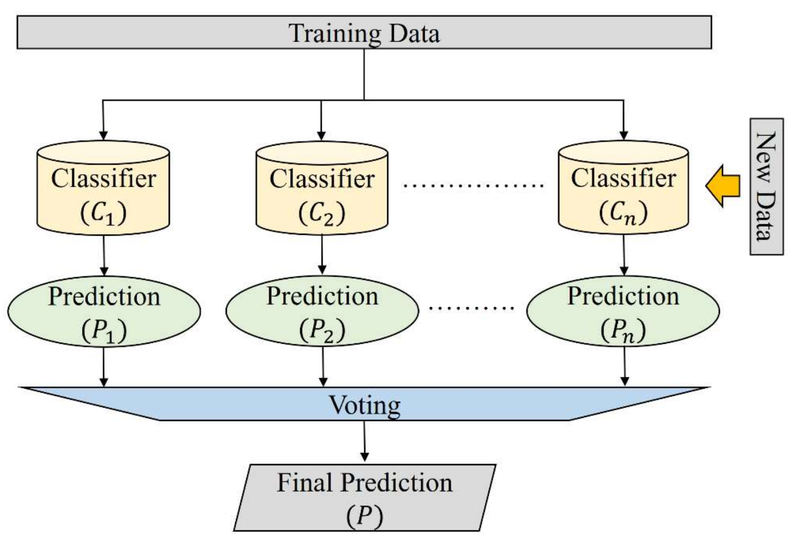


Figure 5.6: Majority voting classifier

Majority voting classifier is basically a kind of decision rule which chooses one with maximum votes among numerous available choices. In this approach, each model gives its prediction with the same rights corresponding to every test sample. Final prediction shall be the prediction with maximum votes as compared with others. It may be referred as plurality-voting scheme.

Let $S_{m,n}$ denotes the distance of a test sample from m^{th} class borderline considering n^{th} classifier. So, finally predicted class can be expressed as given in the Eq. 5.14 (Gupta et al., 2018) :

$$P = \max_{n} count\{P_n\}\ , where\ P_n = arg\ \max_{m}\{S_{m,n}\} \tag{5.14}$$

Finally, it gives the predicted class that shall have the most occurring score for a particular test sample. Thus, this technique is effective in reducing the impact of errors made by individual classifiers and can improve the overall accuracy of the handwritten word recognition system. It helps to overcome the limitations of any single classifier and leverages the collective decision-making power of multiple classifiers to make a more reliable prediction.

5.4 EXPERIMENTAL RESULTS AND DISCUSSION

In order to analyze the performance of handwritten Devanagari word recognition system, an analytical study of different combinations of features and classifiers are carried out in terms of various performance evaluation metrics. In this section, extensive experimentation which has been carried out to evaluate and analyze the performance of handwritten Devanagari word recognition system for various feature extraction and classification techniques is discussed. The system has been evaluated using in-house database of 48,000 handwritten Devanagari words. Authors have taken 80% of the data as training (38,400 words) and 20% data as testing samples (9,600 words). The metrics considered for this experimental work include Recognition Accuracy (RA), False Acceptance Rate (FAR), False Rejection Rate (FRR), Precision (PR), F1-Score (FS), Matthew's Correlation Coefficient (MCC) and Area Under the Curve (AUC). Experiment results in terms of above mentioned metrics are presented in Tables 5.1 to 5.7 along with their graphical representation in Figs. 5.7 to 5.13.

5.4.1 Performance Analysis based on Recognition Accuracy (%)

Table 5.1 shows experimental results in terms of Recognition Accuracy (%) for various features and classifiers combination. Minimum recognition accuracy of 76.76% is achieved using Elliptical features and MLP classification using the corpus of handwritten Devanagari words.

Table 5.1: Performance analysis based on recognition accuracy (%)

Feature Extraction Techniques	Classification Techniques			
	Support Vector Machine (SVM)	Multi-Layer Perceptron (MLP)	Extreme Learning Machine (ELM)	Majority Voting (MV)
Intersection & open-end point-based features (FB1)	81.52%	77.46%	79.26%	83.67%
Elliptical features (FB2)	79.76%	76.76%	82.96%	83.81%
Arnold transform based features (FB3)	81.73%	78.93%	83.28%	84.63%
FB1 + FB2	82.81%	77.77%	83.53%	85.94%
FB1 + FB3	83.66%	79.83%	84.23%	84.89%
FB2 + FB3	81.98%	79.48%	83.89%	87.65%
FB1 + FB2 + FB3	84.35%	80.83%	83.98%	88.06%

Illustration of recognition accuracy (%) vs. feature extraction and classification techniques considered are presented graphically in Fig. 5.7. It indicates that majority voting classifier performs better as compared with other classification techniques for handwritten Devanagari word recognition. Whereas, MLP based classification has achieved lower recognition accuracy (%) for various features considered in this work.

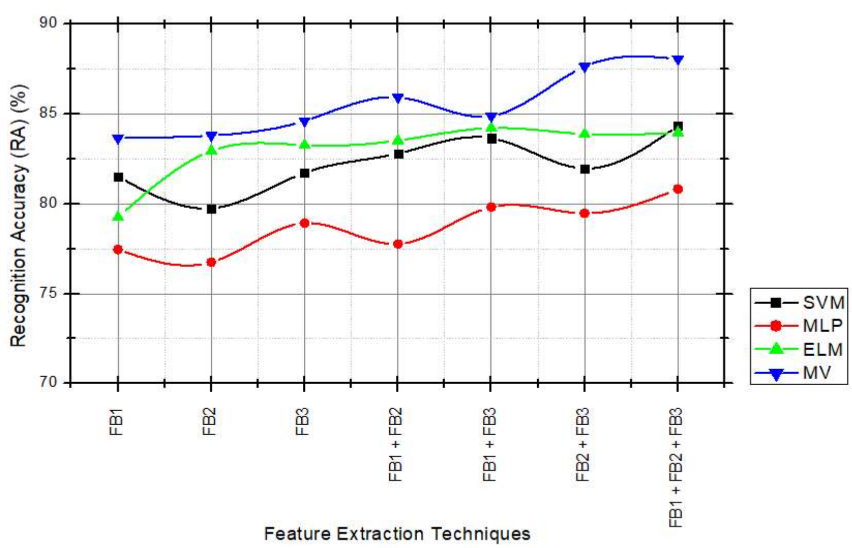


Figure 5.7: Illustration of recognition accuracy (%) vs. feature extraction and classification techniques considered

It has been analyzed that using combination of various feature extraction techniques (FB1 + FB2 + FB3) along with majority voting classifier recognition accuracy has been improved up to 88.06%.

5.4.2 Performance Analysis based on FAR (%)

Experimental results in terms of False Acceptance Rate (FAR) are presented in the Table 5.2. It indicates that Elliptical feature extraction technique along with MLP classifier has obtained maximum FAR of 0.19%. Whereas, with the combination of features viz. (FB2+FB3) and (FB1+FB2+FB3) along with majority classification gave minimum FAR of 0.10% as depicted in the Fig. 13.

Table 5.2: Performance analysis based on FAR (%)

Feature Extraction Techniques	Classification Techniques			
	Support Vector Machine (SVM)	Multi-Layer Perceptron (MLP)	Extreme Learning Machine (ELM)	Majority Voting (MV)
Intersection & open-end point-based features (FB1)	0.15%	0.18%	0.17%	0.13%
Elliptical features (FB2)	0.17%	0.19%	0.14%	0.13%
Arnold transform based features (FB3)	0.15%	0.17%	0.14%	0.12%
FB1 + FB2	0.14%	0.18%	0.13%	0.11%
FB1 + FB3	0.13%	0.16%	0.13%	0.12%
FB2 + FB3	0.15%	0.17%	0.13%	0.10%
FB1 + FB2 + FB3	0.13%	0.16%	0.13%	0.10%

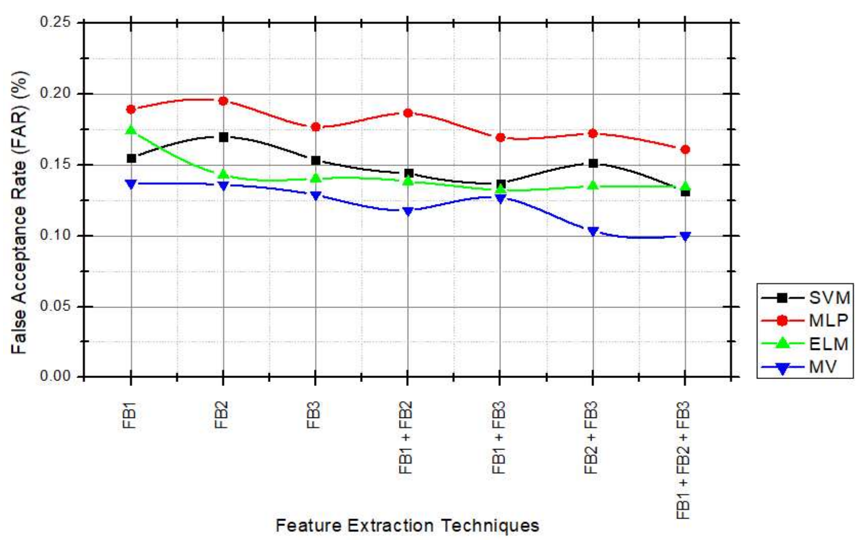


Figure 5.8: Illustration of false acceptance rate (%) vs. feature extraction and classification techniques considered

5.4.3 Performance Analysis based on FRR (%)

Table 5.3 presents the False Rejection Rate (FRR) (%) results for different combinations of feature extraction techniques and classification techniques considered for handwritten word recognition system.

Table 5.3: Performance analysis based on FRR (%)

Feature Extraction Techniques	Classification Techniques			
	Support Vector Machine (SVM)	Multi-Layer Perceptron (MLP)	Extreme Learning Machine (ELM)	Majority Voting (MV)
Intersection & open-end point-based features (FB1)	18.47%	22.53%	20.73%	16.32%
Elliptical features (FB2)	20.23%	23.23%	17.03%	16.18%
Arnold transform based features (FB3)	18.26%	21.06%	16.71%	15.36%
FB1 + FB2	17.18%	22.22%	16.46%	14.05%
FB1 + FB3	16.33%	20.16%	15.76%	15.10%
FB2 + FB3	18.01%	20.51%	16.10%	12.34%
FB1 + FB2 + FB3	15.64%	19.16%	16.01%	11.93%

Among the feature extraction techniques, the combination of features (FB1+FB2+ FB3) achieved the lowest False Rejection Rate (FRR) of 11.93% with the Majority Voting (MV) classification technique. This is followed by the combination of (FB2+FB3) with a False Rejection Rate (FRR) of 12.34%. When considering the classification techniques, the Majority Voting (MV) consistently outperforms the other classifiers in terms of FRR. SVM and MLP achieve relatively higher FRR values ranging from 18.47% to 23.23%, while ELM shows slightly better performance with FRR values ranging from 16.01% to 20.73%.

Fig. 5.9 presents an illustration of the False Rejection Rate (FRR) (%) versus various feature extraction and classification techniques considered in this study. The results indicate that combining multiple feature extraction techniques can lead to lower False Rejection Rates, indicating improved recognition accuracy in the handwritten word recognition system. The Majority Voting (MV) classifier, which combines the decisions of multiple classifiers, demonstrates its effectiveness in reducing the FRR. Therefore, improving the overall performance and reliability of the system.

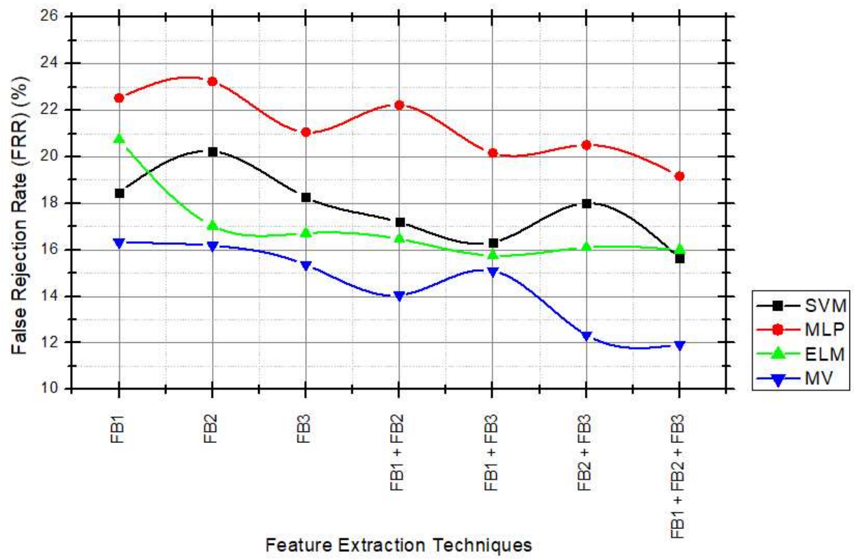


Figure 5.9: Illustration of false rejection rate (%) vs. feature extraction and classification techniques considered

5.4.4 Performance Analysis based on Precision (%)

The performance analysis of the HWR system in terms of Precision (PR) (%) is presented in the Table 5.4. From the experimental results, it can be observed that the combination of feature extraction techniques (FB1+FB2+FB3) gave the highest Precision scores across all classification techniques.

Table 5.4: Performance analysis based on precision (%)

Feature Extraction Techniques	Classification Techniques			
	Support Vector Machine (SVM)	Multi-Layer Perceptron (MLP)	Extreme Learning Machine (ELM)	Majority Voting (MV)
Intersection & open-end point-based features (FB1)	82.33%	78.62%	80.22%	84.59%
Elliptical features (FB2)	80.71%	77.94%	83.76%	84.72%
Arnold transform based features (FB3)	82.56%	79.98%	84.12%	85.51%
FB1 + FB2	83.63%	78.89%	84.40%	86.80%
FB1 + FB3	84.57%	80.77%	85.14%	85.78%
FB2 + FB3	82.87%	80.44%	84.79%	88.44%
FB1 + FB2 + FB3	85.23%	81.67%	84.88%	88.83%

This combination yields a Precision of 85.23% with SVM, 81.67% with MLP, 84.88% with ELM and 88.83% with Majority Voting (MV). Among the individual feature extraction techniques, FB1 consistently shows promising results, with Precision scores ranging from 78.62% to 84.59% across the classification techniques. FB2 and FB3 also demonstrate competitive performance, with Precision scores ranging from 77.94% to 84.72% and 79.98% to 85.51%, respectively. Furthermore, it is worth noting that the Majority Voting (MV) classifier consistently achieves the highest Precision scores when combined with different feature extraction techniques as shown in Fig. 5.10.

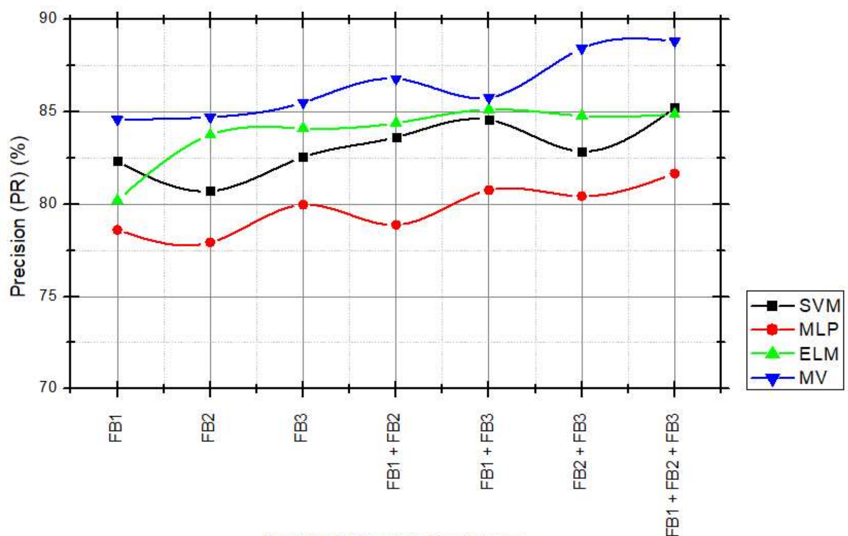


Figure 5.10: Illustration of precision (%) vs. feature extraction and classification techniques considered

5.4.5 Performance Analysis based on F1-Score (%)

The performance analysis of the handwritten word recognition system based on F1-Score (%) is presented in the following Table 5.5. The results show that the combination of feature extraction techniques (FB1+FB2+FB3) consistently achieves the highest F1-Scores across all classification techniques. This combination yields F1-Scores of 84.52% with SVM, 81.00% with MLP, 84.17% with ELM and 88.20% with Majority Voting (MV).

It can also be seen from Fig. 5.11 that the Majority Voting (MV) classifier consistently achieves the highest F1-Scores when combined with different feature extraction techniques. This indicates that the ensemble approach of combining multiple classifiers improves the recognition system's overall accuracy.

Table 5.5: Performance analysis based on F1-Score (%)

Feature Extraction Techniques	Classification Techniques			
	Support Vector Machine (SVM)	**Multi-Layer Perceptron (MLP)**	**Extreme Learning Machine (ELM)**	**Majority Voting (MV)**
Intersection & open-end point-based features (FB1)	81.67%	77.72%	79.46%	83.86%
Elliptical features (FB2)	79.95%	77.02%	83.13%	83.99%
Arnold transform based features (FB3)	81.90%	79.14%	83.45%	84.80%
FB1 + FB2	82.97%	78.02%	83.70%	86.11%
FB1 + FB3	83.85%	80.01%	84.42%	85.07%
FB2 + FB3	82.15%	79.68%	84.07%	87.79%
FB1 + FB2 + FB3	84.52%	81.00%	84.17%	88.20%

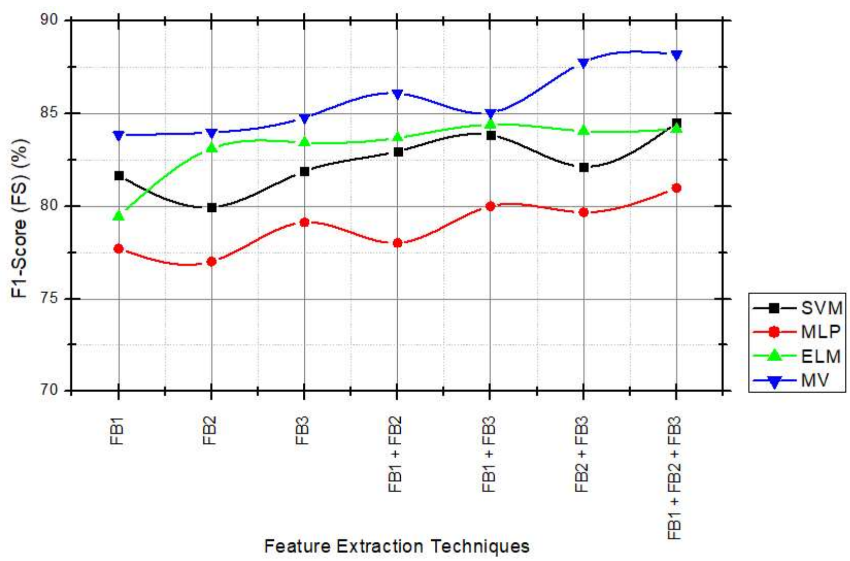


Figure 5.11: Illustration of F1-Score (%) vs. feature extraction and classification techniques considered

5.4.6 Performance Analysis based on MCC (%)

The performance analysis of HWR system in terms of the Matthew's Correlation Coefficient (MCC) is presented in Table 5.6. It can be observed from the given table that the combination of feature extraction techniques (FB1+FB2+FB3) consistently achieves the highest MCC values across all classification techniques. This combination yields MCC values of 0.845 with SVM, 0.809 with MLP, 0.841 with ELM, and 0.882 with Majority Voting (MV). The graphical representation of Matthew's Correlation

Coefficient (MCC) versus feature extraction and classification techniques considered work has been given in Fig. 5.12.

Table 5.6: Performance analysis based on MCC

Feature Extraction Techniques	Classification Techniques			
	Support Vector Machine (SVM)	Multi-layer Perceptron (MLP)	Extreme Learning Machine (ELM)	Majority Voting (MV)
Intersection & open-end point-based features (FB1)	0.816	0.776	0.794	0.838
Elliptical features (FB2)	0.799	0.769	0.831	0.839
Arnold transform based features (FB3)	0.818	0.791	0.834	0.848
FB1 + FB2	0.829	0.779	0.837	0.861
FB1 + FB3	0.838	0.799	0.844	0.850
FB2 + FB3	0.821	0.796	0.840	0.878
FB1 + FB2 + FB3	0.845	0.809	0.841	0.882

Figure 5.12: Illustration of Matthew's correlation coefficient vs. feature extraction and classification techniques considered

5.4.7 Performance Analysis based on AUC (%)

Experimental results in terms of Area Under the Curve (AUC) for HWR system is given in the Table 5.7. It can be observed that maximum AUC of 93.98% was achieved using combination of the all three features (FB1+FB2+FB3) with majority voting classifier.

While minimum AUC of 88.28% is obtained when considering Elliptical features (FB2) and Multi-layer Perceptron (MLP) classification technique.

Table 5.7: Performance analysis based on AUC (%)

Feature Extraction Techniques	Classification Techniques			
	Support Vector Machine (SVM)	Multi-layer Perceptron (MLP)	Extreme Learning Machine (ELM)	Majority Voting (MV)
Intersection & open-end point-based features (FB1)	90.68%	88.63%	89.54%	91.76%
Elliptical features (FB2)	89.79%	88.28%	91.41%	91.83%
Arnold transform based features (FB3)	90.91%	89.65%	91.88%	93.77%
FB1 + FB2	91.33%	88.79%	91.69%	92.91%
FB1 + FB3	91.76%	89.83%	92.05%	92.38%
FB2 + FB3	90.79%	89.38%	91.57%	92.25%
FB1 + FB2 + FB3	92.11%	90.33%	91.92%	93.98%

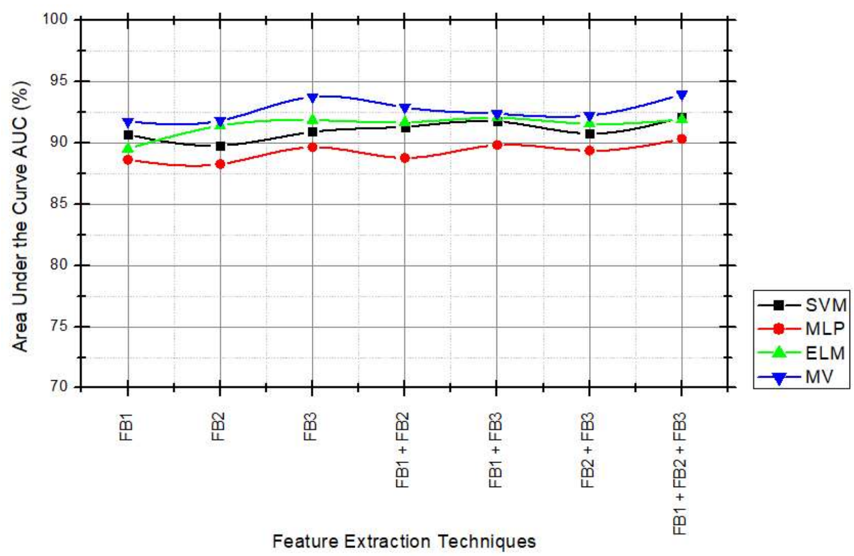


Figure 5.13: Illustration of area under the curve vs. feature extraction and classification techniques considered

It is concluded from Fig. 5.13 that AUC results attained using combination of the all three mentioned features (FB1+FB2+FB3) along with majority voting classifier are better than individual features.

5.5 COMPARISON WITH THE STATE-OF-THE-ART METHODS AND SYNTACTIC ANALYSIS

For the handwritten Devanagari word recognition system, experimental results are given in Tables 5.1 to 5.7. The graphical illustrations of the experimental results in terms of various performance evaluation metrics are described in Figs. 5.7 to 5.13. Comparison with existing holistic approach based methodologies developed for handwritten Devanagari words are carried out with the proposed method and is presented in Table 5.8.

Table 5.8: Comparison with existing holistic approach based methodologies

Authors	Feature Extraction Techniques	Classification Techniques	Recognition Accuracy (%)
Shaw et al., (2008a)	Histogram of Chain Code Directions-based	HMM	80.20%
Patil and Ansari, (2014)	Android Technology-based on Gesture Class	HMM	(a) 96% *(for 50 words)* (b) 94% *(for 100 words)*
Shaw et al., (2015)	DDD and GSC-based	Multiclass SVM	88.75%
Kumar, (2016)	Chain Codes, Cumulative Histograms, Gradient, Neighbor Pixel Weight-based	MLP	(a) 80.8% *(for Two Character Words)* (b) 72.0% *(for Six Character Words)*
Proposed Method	Combination of Intersection & Open-End Point, Elliptical and Arnold Transform-based	Majority voting	88.06%

It has been gathered from literature that various features and classifiers have been used by various researchers for the recognition of handwritten words. Also, illustration of confusion matrix is given in Fig. 5.14, where a combination of the three features namely Intersection & open-end point-based, Elliptical and Arnold transform based features i.e. (FB1+FB2+FB3) have been considered along with majority voting classifier. It gives the correlation between predicted handwritten word (predicted class) and actual handwritten word (actual class). It can be seen from Table 5.8 and Figure 5.14 that proposed method has achieved acceptable level of recognition accuracy. In practice, many times single feature extraction or classification technique is not suitable to achieve desirable accuracy level. In such scenario, combination of multiple features and classifiers can be used to improve recognition accuracy significantly.

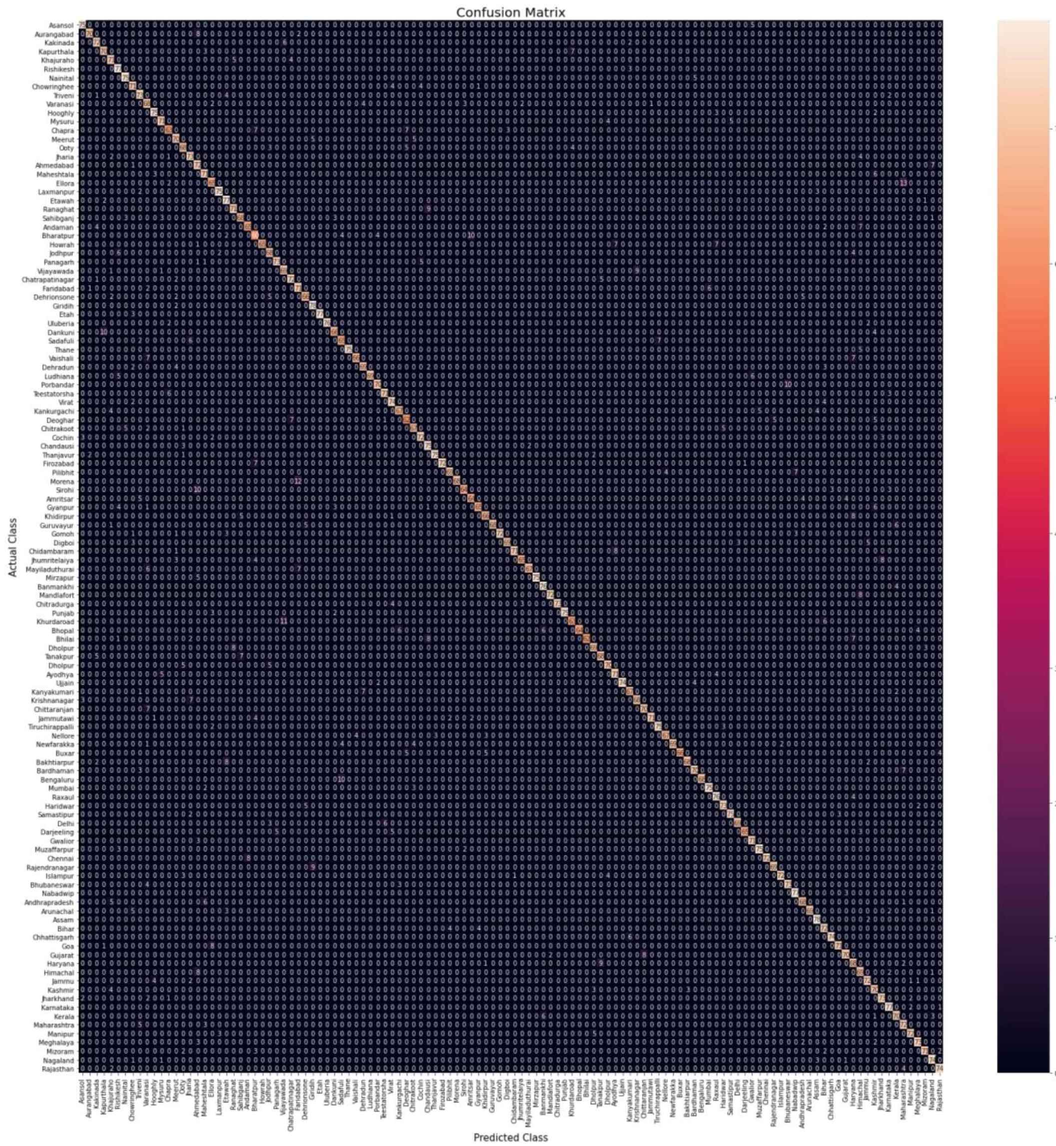


Figure 5.14: Illustration of confusion matrix

5.6 CHAPTER SUMMARY

This chapter presents an analytical study of various features and classifiers for handwritten Devanagari word recognition in holistic manner. For this, various features namely intersection & open-end points features, elliptical features and Arnold transform based directional features are explored along with their different combinations. Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), Extreme Learning Machine (ELM) and Majority Voting (MV) Classifiers are used for recognizing the handwritten Devanagari words. From the experimental study, recognition accuracy of 88.06%, false acceptance rate of 0.10%, false rejection rate of

11.93%, precision of 88.83%, F1-Score of 88.20%, Matthew's correlation coefficient of 0.882 and area under the curve of 93.98% are obtained using combination of above three mentioned features and majority voting classifier by considering a corpus of 48,000 samples. This indicates good performance of studied framework. Moreover, the experimental results are compared with some state-of-the-art techniques and results are better or comparable with existing methods.