

ON STUDYING HANDWRITTEN DEVANAGARI WORD RECOGNITION SYSTEM BASED ON GRADIENT AND STRUCTURAL FEATURES

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Abstract: This paper introduces a method for the recognition/identification of the offline handwritten Devanagari words, which has a variety of pattern recognition applications including such as cheque reading, airline ticket readers, bill processing systems, handwritten address interpretation, signboard translation and postal automation. The proposed framework uses a holistic approach for the recognition/identification of Devanagari handwritten words. It considers, a complete word as an individual entity for recognition i.e. without using segmentation. Gradient and structural features based on contour-directional histogram are extracted from the handwritten word images. Three different classifiers namely SVM (Support Vector Machine), NB (Naive Bayes) and XGBoost (eXtreme Gradient Boosting) are used for the recognition tasks. Experiments are also carried out using combined feature vectors resulted from gradient and structural features as input to various classifiers. The framework is evaluated on the corpus of 20,000 words of 50-different town names handwritten in Devanagari script. The presented work is subjected to performance evaluation in terms of PR (Precision), FAR (False Acceptance Rate), FRR (False Rejection Rate), and RA (Recognition Accuracy). It has gathered from experimental work that combination of feature vectors resulted from gradient and structural features along XGBoost classifier perform better as compared with individual features itself.

Keywords: Handwritten word recognition; holistic approach; feature extraction; classification

1. Introduction

HWR (Handwritten Word Recognition) is an active and challenging topic/issue of computer vision and pattern recognition. It is because of its variety of applications including recognition of ancient document, digital-character conversion, keyword-spotting, text-to-speech conversion and postal automation [1-3]. HWR enables the computer to identify handwritten words written in natural handwriting. HWR approaches can be classified as offline-HWR and online-HWR approaches [4]. Online-HWR approach based systems use electronic surface whereas offline-HWR approach based systems use paper like surface for writing purpose. Further, offline-HWR approaches can be categorized into analytical (segmentation-based) and holistic (without segmentation-based) approaches. Analytical approaches initially divide the

whole word into individual characters using suitable segmentation phase and thereafter, words are recognized hence called segmentation based approaches. Whereas, holistic approaches treat the complete word as an individual/single entity without using explicit segmentation. Therefore, these are also called as segmentation free approaches. In the past years, many researchers have worked on analytical based approaches as compared with holistic approaches for recognition of handwritten words written in Devanagari script. Very few work has been carried out using holistic based approaches [2]. In this work, a framework for holistic approach based offline HWR has been explored for Devanagari script.

Nowadays, researchers are working for recognition of words (handwritten) written in various scripts by considering holistic based approaches. Like in [5], authors recognized words (Devanagari) by taking stroke based features (statistical and structural) and HMM (Hidden Markov Model) to attain promising results for small lexicon sized corpus. Shaw et al. (2008a;2008b) in their articles [6, 7] achieved 80.2% and 84.31% of recognition accuracies using directional chain code and stroke based features on a corpus of 39,700 words, respectively. Shaw and Parui achieved 85.57% (testing) and 91.25% (training) accuracies for recognition words (50-Devanagari words) using wavelet transform based feature vectors. They used modified Bayes discriminant function as classifier in the second stage. Singh et al. (2011) achieved 93.21% of accuracy for recognition of their corpus consisting of 28,500 words using curvelet features and KNN classification [8]. Ramachandru et al. (2012) achieved 91.23% of recognition accuracy for their corpus developed from 100 writers. They explored various techniques based on directional features and dynamic programming [9]. Shaw et al. (2015) explored Directional-Distance and Gradient-Structural based features along with their combinations for word recognition [10]. Kumar (2016) gained 80.8% of accuracy for Devanagari word recognition system based on gradient features and MLP (Multi-Layer Perceptron) classifier [11]. Malakar et al. (2017) extracted various features such as aspect ratio, centroid and projection length etc. from word images and obtained 96.82% of success rate using MLP classification [12].

Bhunia et al. (2018) presented a system for text recognition for three scripts namely Bangla, Devanagari and Gurumukhi along with word spotting [13]. They used zone-wise mapping of characters for better learning. Ghosh et al. (2019) used wrapper-filter approach and MLP algorithm for classification of Bangla words [14]. They extracted gradient, statistical and contour based features from Bangla word images and scored 93% of accuracy. Malakar et al. (2020) extracted local as well as global features of handwritten word images. They developed a model based on Hierarchical Feature Selection (HFS) and achieved 95.30% of accuracy [15]. Kaur and Kumar (2021a) extracted various statistical features from handwritten Gurumukhi words [16]. They obtained 91.66% of recognition accuracy using zoning feature vector and XGBoost classification approach. Other sections of the paper is presented as follows: section-2 presents data collection and proposed methodology of this work. Various techniques of feature extraction are given in section-3. Section-4 gives overview of classification techniques used in this article. Experimental results along with performance metrics are

mentioned in section-5. Conclusions are made along with suggestions for the future in section 6.

2. Data Collection and Methodology

To develop the framework for the recognition of handwritten Devanagari words, firstly a corpus of Devanagari words have been generated. Thereafter, performance analysis of proposed framework has been done in terms of various performance metrics on the basis of collected corpus of handwritten words.

2.1 Dataset

Due to lack of standard database, authors have collected a corpus of 20,000 handwritten words (50 classes) written in Devanagari script by hundreds of writers. For experimental work, fifty different town names written in Devanagari script are considered as mentioned in [5-7]. Sample of handwritten Devanagari words collected as a corpus is depicted in Figure 1. These words has been collected on A-4 sized papers, then scanned at 300dpi for their digitization and thereafter, resized into uniform size of 256×64 due to horizontal style of writing the Devanagari script. The corpus has been divided using ratio of 70% and 30% data in training/testing sets i.e. 14,000 words as training-dataset and 6,000 words as testing-dataset.

आसनसोल	हुगली	इटावा	फरीदाबाद	लुधियाना
औरंगाबाद	मैसूर	राणघाट	डेहरीओनसोन	पोरबंदर
कांकीनडा	छपरा	साहिबगंज	गिरिडीह	तिसतातोरसा
कपूरथला	मेरठ	अंझमान	पटा	विराटि
खजुराहो	ऊटी	भरतपुर	उलबेडिया	काकरगाछी
ऋषिकेश	झरिया	हावड़ा	डानकुनी	देवघर
मैनीताल	अहमदाबाद	जोधपुर	सेक्डाफुलि	चिक्कूर
चौरंगी	महेशतला	पानागढ़	थाने	कोचीन
त्रिवेणी	पल्लौरा	विजयवाड़ा	वैशाली	चंदौसी
वाराणसी	लक्ष्मनपुर	क्षत्रपतीनगर	देहरादून	तंजौर

Figure 1. Sample of handwritten Devanagari words

2.2 Proposed Methodology

The framework is proposed for the development of handwritten Devanagari word recognition system by adopting a step-by-step procedure. The various steps involved include: scanning of handwritten words, digitization and pre-processing, extraction of features so as to construct feature vectors, thereafter classification on the basis of extracted features and finally, evaluation of system performance on the basis of various metrics. The flow chart for the framework is depicted in Figure 2.

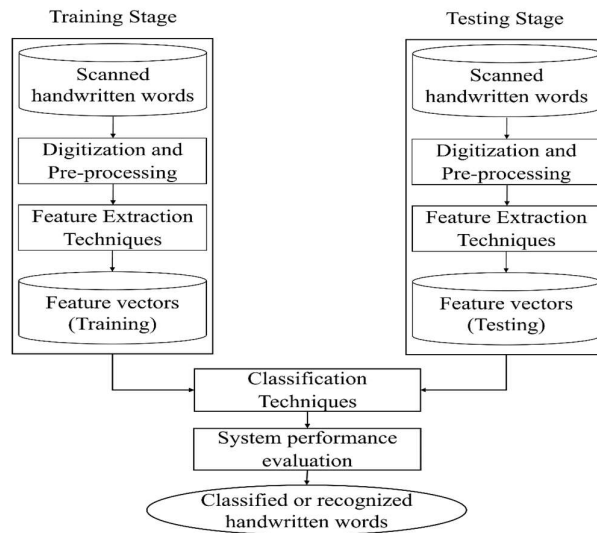


Figure 2. Flow chart for the framework

In the following subsection, the digitization and pre-processing processes are briefly covered.

2.3 Digitization and Pre-Processing

The act of scanning a document and creating an electronic copy of the original document is known as digitization. Digitization gives the binary image and thereafter pre-processing is carried out. In this article, after scanning and cropping of handwritten word images; binarization [17] is used for converting the scanned images into black and white pixels which shall help to minimize the computational complexity. Thereafter, thinning of handwritten word images is carried out using [18] so as to reduce the text width which shall further help to minimize required amount of the data so as to represent/store a word [30]. Figure 2. depicts an example of handwritten word “Rishikesh (ऋषिकेश)” during digitization and preprocessing. Figure 3(a) indicates scanned handwritten word, Figure 3(b) presents the word after binarization, whereas inverted image is given in Figure 3 (c) and finally, after applying thinning, the word is presented in Figure 3(d).

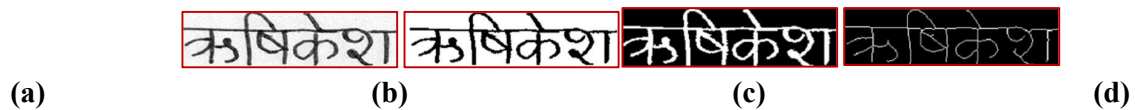


Figure 3. Example of digitization and preprocessing

3. Feature Extraction Techniques

The main aim of feature extraction technique is to extract significant/meaningful and suitable information from input handwritten images so that the same can be used for further classification or recognition purposes. There are various issues and challenges for developing a handwritten word recognition system [2, 19]. Among those, the most significant issue and challenge are the selection of features. As the recognition accuracy of any recognition system is mainly subject to the selection and nature of the extracted features. Therefore, it becomes

desirable to extract meaningful and significant features from handwritten word images. From the literature, it has gathered that directional and structural information of a character or word can act as feature vectors for further classification. In this work, gradient (directional) and structural features are considered for recognition purposes.

3.1 Gradient Feature Extraction

The gradient refers vector quantity that consists of both magnitude and directional components. These components can be computed by differentiation while moving in the direction of horizontal and vertical way [20]. The image-gradient may be calculated by considering a variety of operators, including the Sobel, Robertz, and Prewitt operators. In this work, gradient vector $[G_u, G_v]^T$ is calculated using Sobel operator, where G_u and G_v represents the horizontal-component and vertical-component of the gradient, respectively. To get the distinctive information of the handwritten word image, G_u and G_v are calculated using two marks or templates (horizontal and vertical) of Sobel operator (3×3) as given in the Figure 4.

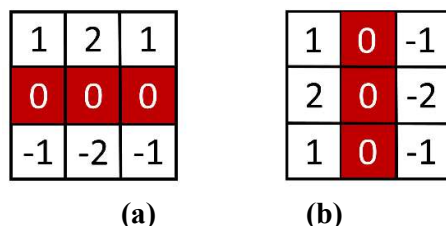


Figure 4. Sobel masks: (a) horizontal and (b) vertical components

For a given handwritten word image (H) of size $M \times N$, an 8-pixel neighborhood at each pixel (i, j) is calculated (where, $i = 1$ to M , and $j = 1$ to N) as shown in Figure 5 and further convolved with above mentioned Sobel marks so as to find out $G_u(u, v)$ and $G_v(u, v)$. Mathematically, it can be written as:

$$G_u(u, v) = H(i - 1, j - 1) + 2 * H(i - 1, j) + H(i - 1, j + 1) - H(i + 1, j - 1) - 2 * H(i + 1, j) - H(i + 1, j + 1)$$

$$G_v(u, v) = H(i - 1, j - 1) + 2 * H(i, j - 1) + H(i + 1, j - 1) - H(i - 1, j + 1) - 2 * H(i, j + 1) - H(i + 1, j + 1)$$

Further, the magnitude and direction of the gradient are calculated as follows:

$$|G(i, j)| = \sqrt{[G_u(i, j)]^2 + [G_v(i, j)]^2}$$

$$\phi(i, j) = \tan^{-1} \left[\frac{G_v(i, j)}{G_u(i, j)} \right]$$

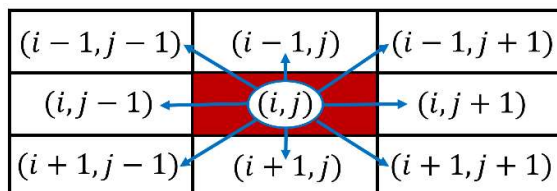


Figure 5. An 8-pixel neighborhood at each pixel (i, j)

In this work, gradient feature vector is created by extraction the gradient information similarly as implemented by [20] for Gurumukhi script.

3.2 Structural Feature Extraction

Structural features represent geometrical and topological features of the handwritten word images using their local and global properties [21]. There are number of structural features depending upon the nature of pattern being classified [22]. In the case of handwritten word recognition tasks, features such as directional histogram based, character/word geometry, intersection of line segments/loops, horizontal/vertical projection profile, structural primitives, left/ right profiles, water reservoir-based features, measurement of cavity regions and feature based on jump/discontinuity in a character or word etc. can be extracted. Basically, these features directly relate the shape of the character/word for recognition purposes [23]. In this work, contour-directional histogram based features are extracted as described by [24] from handwritten Devanagari word images. Pixels of the outer and inner boundary represent the contour of handwritten word images as depicted in the Figure 6. It can be obtained by observing each pixel within a 3×3 window frame.

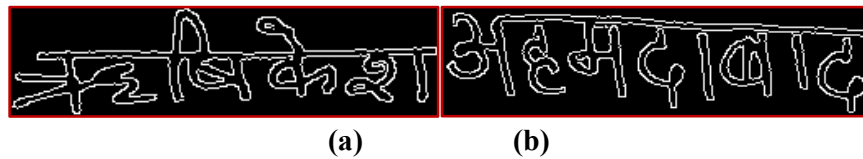


Figure 6. Examples of contour extracted from Devanagari handwritten word images: (a) “Rishikesh (ऋषिकेश)” and (b) “Ahmedabad (अहमदाबाद)”

Further, the resultant contour is split into 64 parts corresponding to the 64 zones (4×16) as given in the Figure 7.

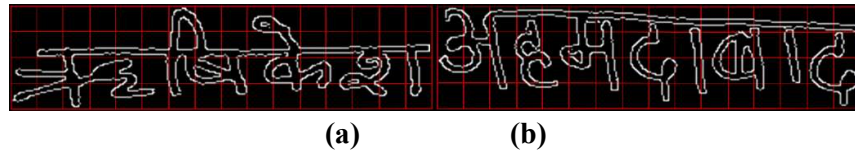


Figure 7. Splitting of contour into 64 parts corresponding to the 64 zones: (a) “Rishikesh (ऋषिकेश)” and (b) “Ahmedabad (अहमदाबाद)”

Thereafter to obtain directional histogram, contour is followed for each of mentioned zones by windowing. Zoning helps to attain local properties or features rather than global features so as to obtain better recognition accuracy.

3.3 Combination of Features

Combination of gradient and structural features are also explored in this article so as to study their effect on recognition accuracy of HWR system. The feature vectors obtained through

gradient and structural based feature extraction techniques as mentioned above, are concatenated to construct another new feature vector.

4. Classification Techniques

Classification techniques are used to recognize the class of unknown word based on the extracted feature vectors. To recognize the unknown word, initially classifier is trained using various training samples. Thereafter, features shall be extracted from testing samples and compared with that of the training sample features so as recognize the class of unknown word. In this article, three classifiers are explored so as handwritten Devanagari words can be recognized. These classifiers are briefly discussed in the following sub-sections.

4.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a machine learning algorithm that creates decision boundary to segregate various classes [4]. The most suitable decision boundary is known as a hyper plane [25]. SVM determines the ideal separation hyper plane for training data by maximizing the margin between the two classes [26], say $(x_j, c_j)_{j=1}^M$, where $x_j \in R^d$ and $c_j \in \{-1, 1\}$ using:

$$\text{Minimizing: } D = \frac{1}{2} m \cdot m + C \sum_{j=1}^M \mu_j$$

$$\text{Subjectto: } c_j(m \cdot x_j + b) \geq 1 - \mu_j, \mu_j \geq 0, \mu_j$$

Here, C represent a parameter to give a trade-off between α and β . Where, α is the minimum training error and β is maximum distance between 2-classes. Support vectors are the data-points that are used to construct optimal hyper plane.

4.2 Naive Bayes (NB)

On Baye's theorem, the Naive Bayes classification method is built where the probability of an event can be expressed in terms of prior information of some event [27]. For handwritten word recognition, this classifier assigns the class label to a handwritten word image depending upon conditional probability. In this work, computation of conditional probability is done on the basis of extracted features from a handwritten word images. For handwritten word recognition system, it firstly builds a probability model (say class d) by considering extracted features of training dataset using following equation:

$$P(z_1, z_2, \dots, z_n | s = d) = \prod_{j=1}^n P(z_j | s = d)$$

After that for computation of conditional probability distribution for the feature vector which shall belong to a particular class, can be carried out as per the following expression:

$$P(s = d | z_1, z_2, \dots, z_n) = \frac{P(s = d) \prod_{j=1}^n P(z_j | s = d)}{P(z_1, z_2, \dots, z_n)}$$

The class S' is estimated for a new feature vector $z' = (z'_1, z'_2, \dots, z'_n)$ during testing phase as per the following expression:

$$S' = \operatorname{argmax}_{d = 1, 2, \dots, n} P(s = d) \prod_{j=1}^n P(z'_j | s = d)$$

This classification algorithm is easier to develop and understand. It is a probabilistic approach and computational time is less. This classifier is highly scalable, learns quickly and uses high dimensional features with limited amount of training data due to independent assumption.

4.3 Extreme Gradient Boosting (XGBOOST)

eXtreme Gradient Boosting (XGBoost) algorithm is an ensemble method which creates decision trees in sequential form. It was developed by [28]. In this, independent variables are assigned with some weights and these weights play significant role during prediction. Initially, similar-weights are given to the whole training-datasets [16]. The likelihood of the record selected by the decision tree for the training drive is represented by the weights. Because, these weights are same initially, hence the probability of record-selection is equal for all. Prediction can be done after training the model. Secondly, all concerned weights shall be updated whose prediction is wrong (weak classifier). This is a significant step in XGBoost. This process of weight updation continues sequentially from one classifier to other classifier, up to Nth decision tree. All weak classifiers are combined to get final class record. Lastly, according to the highest number of comparable recognitions made by the weak classifiers, as shown in Figure 8, the final classifier classifies the testing samples.

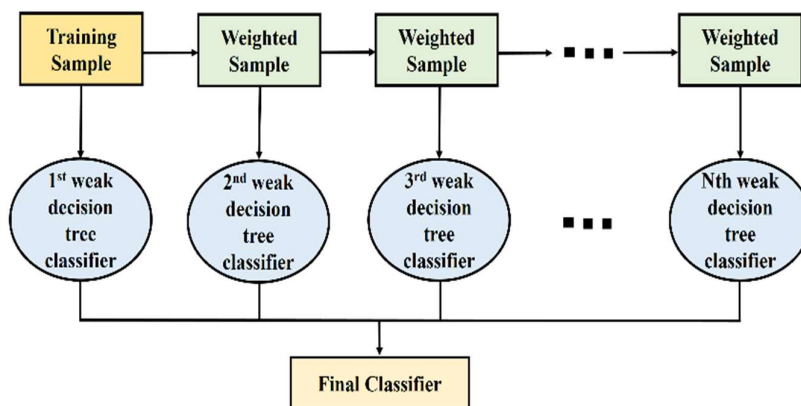


Figure 8. Layout of eXtreme Gradient Boosting (XGBoost)

5. Results and Discussion

5.1 Performance Metrics

Various performance metrics considered for this study are briefly outlined as follows:

- Precision (PR)

It can be calculated as the ratio of True Positive (TP) prediction to the sum of True Positive (TP) and False Positive (FP) predictions. Mathematically, it can be expressed as [16]:

$$PR = \frac{TP}{(TP + FP)} \times 100$$

- False Acceptance Rate (FAR)

It can be calculated as the ratio of False Positive (FP) prediction to the sum of False Positive (FP) and True Negative (TN) predictions. FAR indicates the wrongly accepted, unauthorized instances during recognition or identification [4]. Mathematically, it can be expressed as:

$$FAR = \frac{FP}{(FP + TN)} \times 100$$

- False Rejection Rate (FRR)

FRR can be calculated as the ratio of False Negative (FN) prediction to the sum of False Negative (FN) and True Positive (TP) predictions. It indicates the wrongly rejected, unauthorized instances during recognition or identification [4]. Mathematically, it can be expressed as:

$$FRR = \frac{FN}{(FN + TP)} \times 100$$

- Recognition Accuracy (RA)

The number of successfully predicted or identified samples to the total number of input samples may be used to compute Recognition Accuracy (RA) [4, 14]. It can be expressed as follows:

$$RA (\%) = \frac{n(\alpha)}{n(\beta)} \times 100$$

Where:

$n(\alpha)$: test samples that are correctly recognized or identified.

$n(\beta)$: total test samples.

Experimental results for recognition of handwritten Devanagari words, in terms of above mentioned performance metrics are given and briefly discussed in the following subsection.

5.2 Experimental Results and Discussion

To examine the performance of handwritten Devanagari word recognition system, experimentation has been carried out using Python platform installed with various machine learning libraries such as Keras and Tensorflow etc. Due to the lack of standard dataset [29], in present work, authors have considered a corpus of 20,000 collected handwritten Devanagari words as dataset. The dataset is divided into 14,000 training words (70% of dataset) and 6,000 testing words (30% of dataset). In this article, two feature extraction techniques namely gradient and structural feature extraction techniques along with their combination are explored by considering three classifiers namely Support Vector Machine (SVM), Naïve Bayes (NB) and eXtreme Gradient Boosting (XGBoost). System performance in terms of various performance metrics such as Precision (PR), False Acceptance Rate (FAR), False Rejection Rate (FRR) and Recognition Accuracy (RA) are given in Tables 1 to 4. Graphical representation of system performance are also presented in the Figures 9 to 12.

Table 1: System performance in terms of Precision

Classification Techniques

Feature Extraction Techniques	SVM	NB	XGBoost
Gradient Feature Extraction (F1)	84.31%	86.90%	88.46%
Structural Feature Extraction (F2)	84.78%	87.86%	90.65%
Combination of Gradient and Structural Features (F1+F2)	86.84%	89.04%	90.55%

Experimental results are discussed in the following subsection:

5.2.1 System performance using SVM classifier

By employing Support Vector Machine (SVM) classification, maximum Precision (PR) of 86.84% has been attained by merging both gradient and structural features (F1+F2), as depicted in Table 1. The minimum FAR and FRR reported are 0.29% and 14.26% for combination of gradient and structural features (F1+F2), respectively (refer Table 2 and 3). The maximum Recognition Accuracy (RA) achieved is 85.73% based on combination of gradient and structural features (F1+F2). It can also be observed from Figure 9 and Figure 10 that SVM classification has achieved higher values of False Acceptance Rate (FAR) and False Rejection Rate (FRR) as compared with other classifiers namely Naive Bayes (NB) and eXtreme Gradient Boosting (XGBoost) except for Gradient feature extraction (F1) with NB classification which is 0.30% of FAR and 14.51 of FRR, respectively. Figure 11, shows graphical representation of recognition accuracies in terms of percentage.

Table 2: System performance in terms of FAR

Feature Extraction Techniques	Classification Techniques		
	SVM	NB	XGBoost
Gradient Feature Extraction (F1)	0.35%	0.30%	0.25%
Structural Feature Extraction (F2)	0.34%	0.27%	0.21%
Combination of Gradient and Structural Features (F1+F2)	0.29%	0.24%	0.20%

5.2.2 System performance using NB classifier

The maximum Precision (PR) obtained by using Naive Bayes (NB) classifier is 89.04% as elucidated in Table 1. It has been achieved by combination of gradient and structural features (F1+F2). The minimum FAR and FRR reported are 0.24% and 12.11%, respectively for considering combination of above mentioned two features (refer Table 2 and 3). Naive Bayes (NB) classification achieved maximum Recognition Accuracy (RA) of 87.88% (see Table 4), by considering the combination of gradient and structural features (F1+F2). Graphical

representation has been given in Figure 9 to Figure 11 shows the performance comparison of Naive Bayes (NB) classification as compared with SVM and XGBoost classification.

Table 3: System performance in terms of FRR

Feature Extraction Techniques	Classification Techniques		
	SVM	NB	XGBoost
Gradient Feature Extraction (F1)	17.60%	14.51%	12.48%
Structural Feature Extraction (F2)	16.90%	13.26%	10.25%
Combination of Gradient and Structural Features (F1+F2)	14.26%	12.11%	9.89%

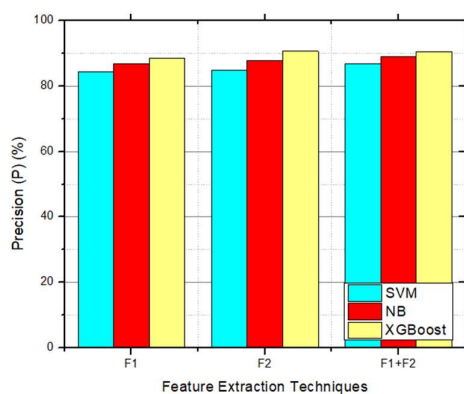


Figure 9. Graphical representation of system performance in terms of Precision (PR)

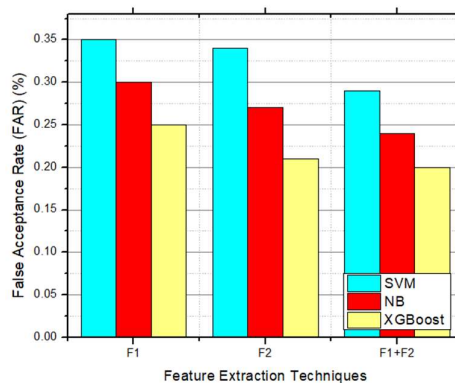


Figure 10. Graphical representation of system performance in terms of False Acceptance Rate (FAR)

5.2.3 System performance using XGBoost classifier

Using eXtreme Gradient Boosting (XGBoost) classification, maximum Precision (PR) of 90.65% has been obtained by structural feature extraction (F2) technique as given in Table 1. Whereas, the minimum FAR and FRR reported are 0.20% and 9.89% for combination of gradient and structural features (F1+F2), respectively (refer Table 2 and 3). The maximum Recognition Accuracy (RA) obtained is 90.10% using combining of gradient and structural features (F1+F2) as depicted in Table 4. Thus, combination of gradient and structural features (F1+F2) gave better results on corpus of handwritten Devanagari words considered for this work, using eXtreme Gradient Boosting (XGBoost) classification. Figure 9 to Figure 11, shows that XGBoost classification achieved better FAR, FRR and RA as compared with other classification methods.

Table 4: System performance in terms of Recognition Accuracy

Classification Techniques	
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Feature Extraction Techniques	SVM	NB	XGBoost
Gradient Feature Extraction (F1)	82.40%	85.48%	87.51%
Structural Feature Extraction (F2)	83.10%	86.73%	89.74%
Combination of Gradient and Structural Features (F1+F2)	85.73%	87.88%	90.10%

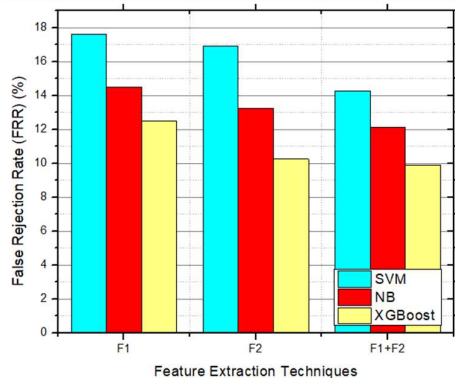


Figure 11. Graphical view of system performance as measured in terms of False Rejection Rate (FRR)

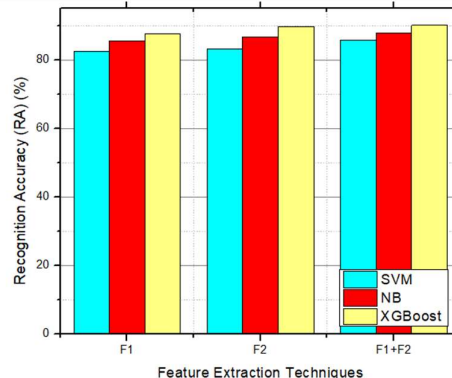


Figure 12. Graphical view of system performance as measured in terms of Recognition Accuracy (RA)

One of the confusion matrix has been depicted in the Figure 13 using combination of gradient and structural features (F1+F2) and XGBoost classification. Class-wise performance for the proposed system of handwritten Devanagari word recognition may be analyzed using the confusion matrix.

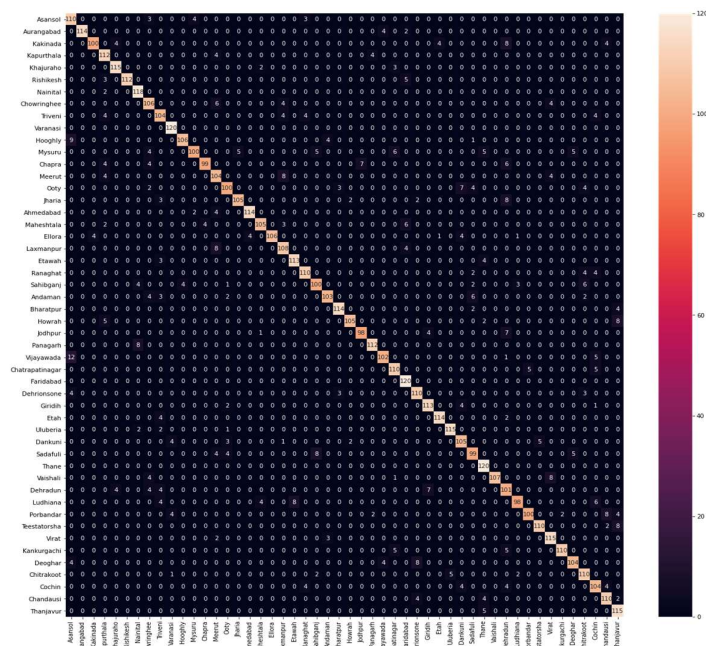


Figure 13. Confusion Matrix

6. Conclusions and Future Scope

This article investigates some techniques for holistically recognizing handwritten Devanagari words. Two features namely gradient as well as structural based features are studied using a corpus of handwritten words (Devanagari). Combination of these two features is also considered to improve the recognition accuracy of the proposed system. For recognition, three classification techniques namely Support Vector Machine (SVM), Naive Bayes (NB) and eXtreme Gradient Boosting (XGBoost) are used due to their robustness. A corpus of handwritten Devanagari words is collected from hundreds of writers belonging to various age groups, geographical backgrounds and qualifications.

Using eXtreme Gradient Boosting (XGBoost) classification, a maximum Recognition Accuracy (RA) of 90.10%, minimum False Acceptance Rate (FAR) of 0.20% and False Rejection Rate (FRR) of 9.89% has been achieved with a combination of gradient and structural features. However, structural based features along with XGBoost classifier attained maximum Precision (PR) of 90.65%. Overall, it has gathered from experimental work that combination of feature vectors resulted from gradient and structural features along XGBoost classifier perform better as compared with individual features itself. But, still there is a scope for improving the recognition results. In future, the size of database (corpus) can be increased and combination of statistical, structural and deep features can be explored to improve the recognition results. Performance of the proposed system can be analyzed for other similar Indian scripts such as Gurumukhi.

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Conflict of Interest: The authors declare that they have no conflict of interest in this work.

Data Availability Statement: Authors have generated own corpus due to lack of standard corpus for handwritten Devanagari words.

Authors Contribution: Sukhjinder Singh: Database collection, methodology and original draft. Naresh Kumar Garg: Supervision, quality check, review and editing.

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