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Script-Based Handwritten Document Classification through Texture Descriptors

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Abstract:
This study presents an innovative approach for page-level script identification in Indian handwritten documents using a combination of Histogram of Oriented Gradients (HOG) and Uniform Local Phase Binary (ULPB) features, coupled with three well-established classifiers: Linear Support Vector Machine (LSVM), k-Nearest Neighbors (KNN), and Linear Discriminant Analysis (LDA). Through rigorous experimentation and evaluation, the proposed method demonstrates superior accuracy and robustness in discerning between diverse script types encountered in Indian documents. This advancement holds significant potential in automating document analysis and retrieval processes, thereby contributing to the preservation and exploration of India's rich cultural and linguistic heritage.

Introduction

With the advancement of digital technologies, the world is undergoing automation and becoming increasingly multilingual. Digital solutions have facilitated easy storage, access, and retrieval of information through digital libraries and document repositories. The rising preference for paperless offices has led to significant research in document image analysis and recognition. Automatic document processing systems heavily rely on two types of content-based information retrieval systems: Optical Character Recognition (OCR) and Keyword spotting without whole document recognition. Both OCR and Keyword spotting play pivotal roles in office automation.

To enhance the efficiency and ease of information retrieval and recognition using OCR or Keyword spotting, prior knowledge of the script used in the documents is beneficial [1, 2, 3]. While Script Identification in Printed Document Images has been largely addressed and considered almost solved [4, 5], the challenge lies in handwritten documents. Handwritten documents are unconstrained in nature, exhibiting variations in writing styles, sizes, strokes, and directions. Consequently, Script-based classification of Handwritten Document Images becomes a highly challenging and complex task, having significant applications in areas such as Google Book Search, Automatic Global Reimbursement, and historical document analysis [6, 7, 10, 11, 12].

India, being a multilingual country with 12 officially recognized scripts and 22 languages, has experienced an exponential growth in technological advancements. The availability of cost-effective image capturing devices like scanners, digital cameras, and smartphones has led to a massive amount of documents awaiting automatic processing, analysis, and information extraction. As per the Indian Constitution, each state can use three scripts for official correspondence. Therefore, the first crucial step is script-based classification of documents. In this chapter, we have benchmarked the Handwritten Script-based classification of documents using two texture descriptors: Histogram of Oriented Gradients and Uniform Local Binary Patterns.

Literature Review

In this section, we review some significant works in the literature related to script and language identification. The journey of the script identification problem traces back to 1994 when researchers began developing basic algorithms based on machine learning and image processing for classifying document images based on script [13, 14, 15]. In [16], the authors presented an algorithm for identifying script-based templates of textual shapes for various scripts, including Armenian, Burmese, Chinese, Cyrillic, Ethiopic, Greek, Hebrew, Japanese, Korean, Roman, and Thai, achieving 90% accuracy with a dataset of 21 documents.

In [17], a method based on Gabor filters and Discrete Cosine Transform was proposed for Printed Word Level Script Identification for 11 official Indian Scripts. The authors of [18] introduced a Document Vectorization Process based on Pixel densities for script and language identification in document images. They carried out language identification for the Latin language and script identification for non-Latin scripts using a template-based technique, heavily dependent on the number of characters and words present in the document. In [19], Script Identification was treated as a Texture Classification problem, and qualitative evaluation of commonly used texture descriptors for script identification was presented. The authors also provided strategies to enhance classification results when limited data is available.

In [20], a tool was developed for identifying scripts at the word level for bilingual dictionary processing. The method employed Gabor filters for feature extraction and used three classifiers (Support Vector Machines (SVM), Gaussian Mixture Model (GMM), and k-Nearest-Neighbor (k-NN)) for script identification. Unconstrained script identification in documents was addressed in [21], using an algorithm that encodes local text structures with scale and rotation invariant codewords representing repeated structures in the document. The method was evaluated with a mixture of handwritten and printed documents.

For page-level script identification of handwritten scripts, the authors in [22] proposed a method for eight popular scripts, namely, Bangla, Devanagari, Gurumukhi, Oriya, Tamil, Telugu, Urdu, and Roman. Modified Log Gabor filters were utilized for feature extraction, and multiple classifiers were employed with a dataset comprising 240 documents. In [23], authors presented a method for page-level script identification in handwritten documents using texture features. Gray Level Co-occurrence Matrix (GLCM) based texture descriptors were extracted and evaluated using four scripts: Bangla, Devanagari, Telugu, and Roman, with a dataset of 120 pages. In [9], a symbolic data analysis-based framework was proposed for handwritten script identification, utilizing a fusion of Gabor, Wavelets, and LBP features with a Symbolic classifier for Kannada, Devanagari, and Roman scripts. More recently, authors in [8] combined visual appearance-based features with morphological features to classify handwritten text pages of different Indian scripts. In [24], an interesting algorithm based on Curvelet transform and Tamura Features was developed for script identification from Asian Scripts in a global context.

From this brief literature review, it is evident that language identification is a crucial problem with a history of more than three decades. Documents are a universal medium for storing information, and scripts serve as the means to encode human-readable information in a scientific graphical form. Consequently, documents are created in various scripts globally, and in a multi-script country like India, one document may consist of multiple scripts or different documents may use different scripts. In such scenarios, script-based classification of documents becomes a critical issue for proper processing and understanding by document processing systems. Therefore, we have undertaken the problem of Script-

Based Classification of Handwritten Documents, focusing on the local context of Karnataka State, which involves three scripts, namely, Kannada, Devanagari, and Roman.

Proposed Method:
Our method involves three basic steps pre-processing, feature computation and classification. In pre-processing, we have binarized and resized the documents to uniform size. Uniform Local Binary Patterns are used for Texture Feature Computation. Support Vector Machine (SVM), Linear Discriminant Analysis (LDA) and K-Nearest Neighbour Classifiers are used in the task of document classification based on script. The diagram of Proposed method is given below for better understanding.

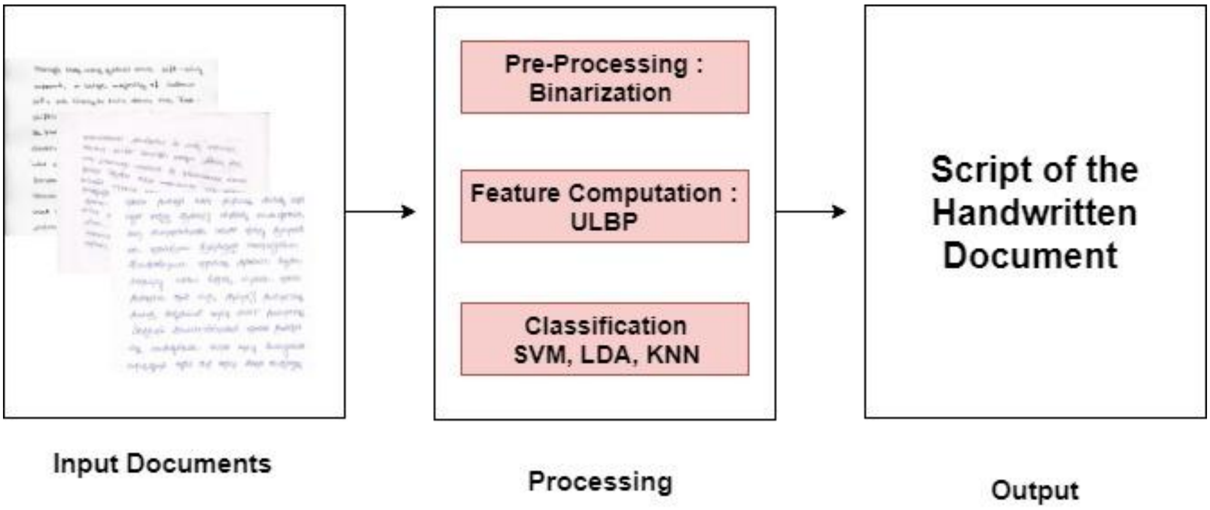

Figure 1. Schematic diagramof our method

Pre-processing:
Pre-processing steps are of utmost importance and hold a significant role in any image processing application, with their specific requirements depending on the application. In our study, we applied binarization to the input documents to represent foreground information like text. To achieve this, we utilized the well-known Otsu's Global Threshold selection method [25] on the gray level image to determine the threshold value for binarization.

Feature Computation:
Effective representation of images with suitable descriptors is a critical step in any image classification algorithm. For our research, we adopted two widely used texture descriptors: Uniform Local Binary Patterns (ULBP) and Histogram of Oriented Gradients [26]. These descriptors have exhibited outstanding performance in various computer vision applications, including Face Recognition, Texture Classification, and Object Detection [27, 28, 29, 30, 31].

Uniform Local Binary Patterns (ULBP):
The Local Binary Pattern technique is an efficient method for describing texture, transforming the input image into an image of integer labels that describe the small-scale spatial texture of the image. In our work, we extended the original LBP approach by considering the bit-wise transitions of binary codes to derive Uniform Local Binary Patterns, which are lower in dimensions and more efficient for the

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classification task. The process of feature computation using ULBP in our work can be summarized as follows:

The input image is converted into a binary image.
A 3x3 window is considered around each pixel as the neighborhood.
If the input binary string has more than 2 transitions, it is considered a non-uniform code; otherwise, it is a uniform code.
Only uniform codes are considered, and a histogram of size 59 is generated as the final feature vector for each document.

The process can be better visualized in the figure below.

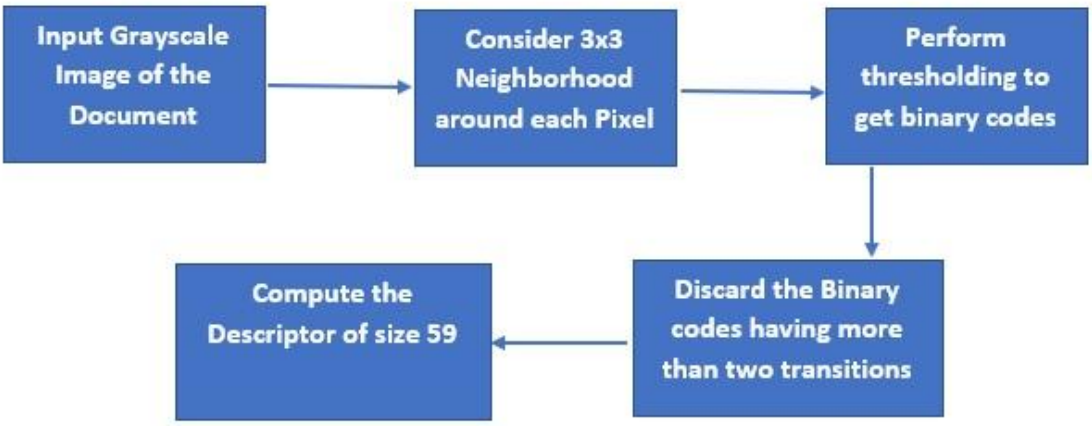

Figure: Procedure to compute Uniform Local Binary Patterns

Histogram of Oriented Gradients (HoG):
In computer vision applications, Histogram of Oriented Gradients (HoG) has gained widespread popularity as a descriptor used for object detection tasks. This technique provides valuable information about the image gradient within locally defined image regions. In our application, the process of generating the HoG-based feature descriptor is as follows:

1. The input document is partitioned into interconnected sections known as cells.
2. For each cell, the magnitude and direction of the gradient are computed.
3. Each cell is then discretized into angular bins based on their orientation.
4. Each pixel within a cell is assigned a gradient weight according to its corresponding angular bin.
5. The cells are grouped based on predefined connectivity, forming blocks.
6. The Histogram of Oriented Gradients is computed for these blocks.
7. The histograms are then normalized to obtain the final descriptor.

In our specific case, we have considered cell sizes of 32x32 and 64x64, resulting in HoG-based feature descriptors of sizes 144 and 1296, respectively. The process of HoG-based feature computation is depicted in the figure below.

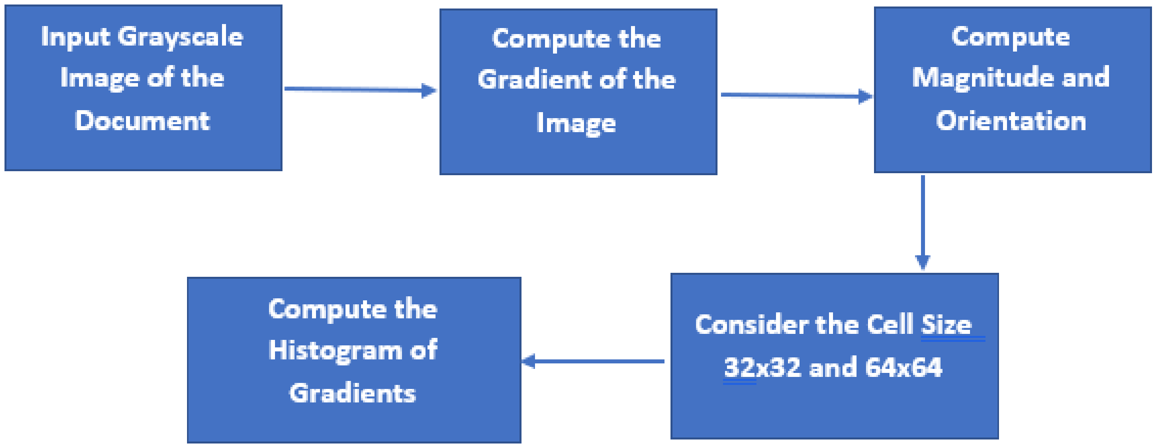

Figure: Procedure to compute histogram of Oriented Gradients

Classifiers:

Support Vector Machines: Support Vector Machine (SVM) is a powerful supervised learning classifier, first introduced by Vapnik [32]. SVM is known for its robustness and efficiency in learning from data. The fundamental principle of SVM lies in constructing a hyperplane with the greatest distance from the nearest data points of any class in the case of linearly separable classes. This approach ensures a strong discriminatory boundary and allows SVM to excel in various classification tasks.

K-Nearest Neighbour Classifier: K-Nearest Neighbor (KNN) is a supervised machine learning algorithm applicable for both classification and regression tasks. Unlike parametric methods, KNN is a non-parametric approach [33], meaning it does not assume any specific data distribution. It is often referred to as a "lazy learning" algorithm because it defers all computations until the classification stage, approximating the function locally based on the nearest neighbors of a given data point. KNN's simplicity and effectiveness make it a fundamental and versatile machine learning technique.

Linear Discriminant Analysis:

Linear Discriminant Analysis (LDA) [34] is a widely used technique in supervised classification, particularly in multiclass scenarios. The primary objective of LDA is to transform the original feature space into a lower-dimensional space while preserving the discriminative information between different classes. This technique is an extension of Fisher's linear discriminant, seeking to identify a linear combination of features that effectively separates two or more classes in the dataset. In addition, LDA is closely related to analysis of variance (ANOVA), further underscoring its significance in statistical analysis and classification tasks.

Experimental Analysis, Results and Discussion:

Dataset: Given the unavailability of a public dataset for script-based document classification, we curated our own dataset focusing on the Kannada and Devanagari Scripts. The data was sourced from native writers proficient in Kannada and Devanagari Script. Each writer was provided with a printed sample text and requested to reproduce it on a white A4-sized page without any specific constraints. To ensure data diversity, the printed texts encompassed various categories such as science, medical, arts and culture, and heritage. Additionally, we engaged volunteers from different age groups and professional backgrounds to collect handwriting data.

A total of 100 documents were collected for each script, involving 50 writers with 2 documents per writer. For the Roman script, we utilized a subset of 100 documents from the publicly available IAM dataset. More detailed information regarding the IAM Database can be found in [35-38]. Sample documents from our dataset are presented in the figure below.

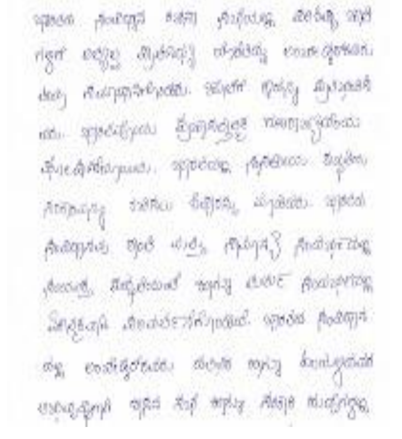	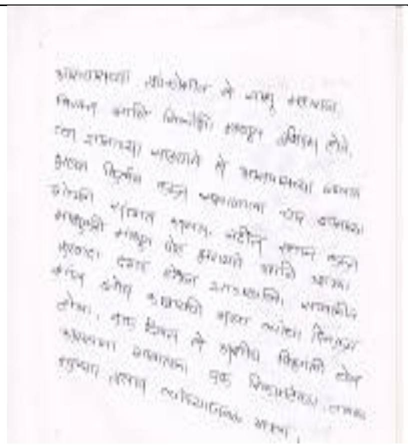	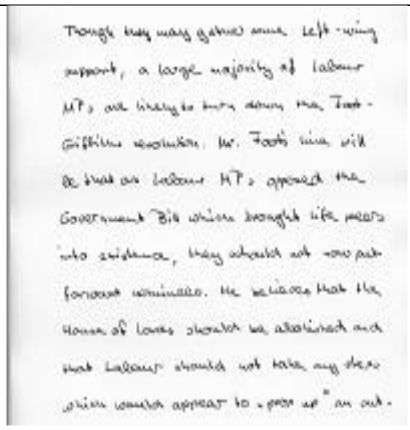
Kannada	Devanagari	Roman

Figure: Sample Document from our dataset

Evaluation Protocol: To evaluate the performance of our method, we employed the k-fold cross-validation technique instead of the conventional training-testing split approach, considering the relatively smaller size of our dataset. The process involved dividing the entire dataset into k subsets. During each iteration, k-1 subsets were used for training, while the remaining kth subset was reserved for testing. This procedure was repeated k times, ensuring that each subset served as both the training and testing set. The final accuracy was determined by calculating the average of the k-accuracies obtained through this process. For our experiments, we set the value of k to be 5. The accuracy metric was defined as follows:

$$\text{Accuracy} = \frac{\text{Correctly Classified Documents in the Class}}{\text{Total Number of Documents in the Class}}$$

Experiments: Our aimed in this work to develop, efficient and robust system for script-based classification of handwritten documents. To achieve this, we have performed different types of experimental test on our dataset as given below:

1. We have evaluated the performance of Uniform Local Binary Patterns with SVM, KNN and LDA
2. We have also tested the HoG with different cell size such as 32x32 and 64x64 and recorded the accuracies with different classifiers under study
3. Computed the confusion matrices for lower accuracies for more deeper understanding
4. We have compared the performance of HoG and ULBP with different classifiers.

In first phase of our experiments, we have computed the 59 dimensions feature vector from each of the document image and give it to different classifiers under study such as SVM, LDA and KNN. We have also observed that, ULBP features have extracted efficient features, from different scripts and are linearly separable, the same is observed from the scatterplot and shown in figure. The detail experimental results based on uniform Local Binary Patterns descriptors for script-based document classification are given in Table 1.

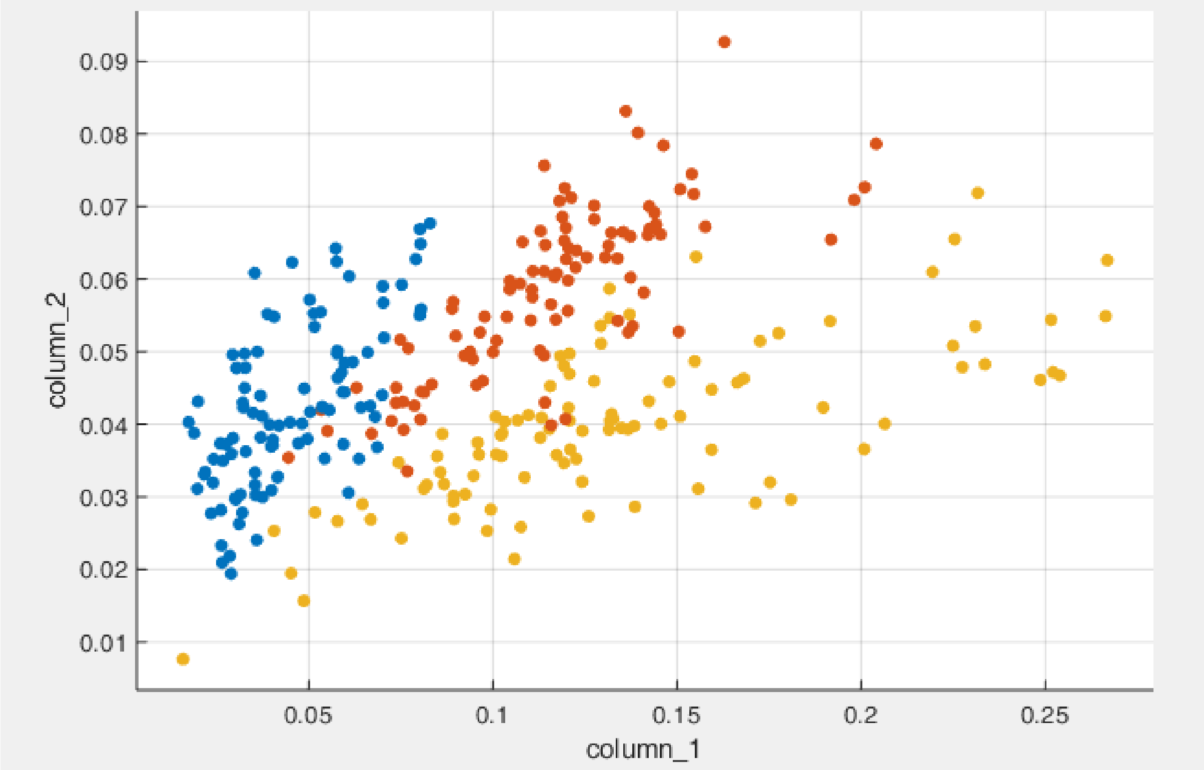

Figure : Scatter Plot of ULBP features representing three different classes of script

Tabel1. Results with ULBP Features for Script Based Handwritten Document Classification

Classifier	**Accuracy**
SVM Cubic	100 %
SVM Linear	100 %
SVM Quadratic	99.70 %
KNN	100 %
LDA	99.30 %

Table 1 illustrates the performance of various classifiers using Uniform Local Binary Patterns (ULBP) features for script-based document classification. Support Vector Machines with Linear Kernel and Cubic Kernel, as well as K-Nearest Neighbors (KNN) classifier, achieved the highest accuracy of 100%. On the other hand, SVM with quadratic kernel and Linear Discriminant Analysis (LDA) exhibited slightly lower accuracies of 99.70% and 99.30%, respectively. Considering the efficiency and excellent performance on the given data, Linear SVM can be considered the optimal choice for future applications of script-based document classification with ULBP features. Although KNN achieved 100% accuracy, it may not be the preferred choice due to the increased number of comparisons and higher memory requirements.

In the second phase of our study, we focused on Histogram of Oriented Gradient (HoG) based features.

We computed feature vectors of dimensions 1296 and 144 from each document image, considering different cell sizes of 32x32 and 64x64, respectively. These fixed-size feature vectors were then utilized as inputs for various classifiers, including SVM, LDA, and KNN. During our analysis, we observed that HoG-based features exhibit more overlapping patterns compared to ULBP and are not as linearly separable. This observation was confirmed through visual inspections of scatterplots, as depicted in the figure. Detailed experimental results based on Histogram of Oriented Gradients for script-based document classification are presented in Table 2.

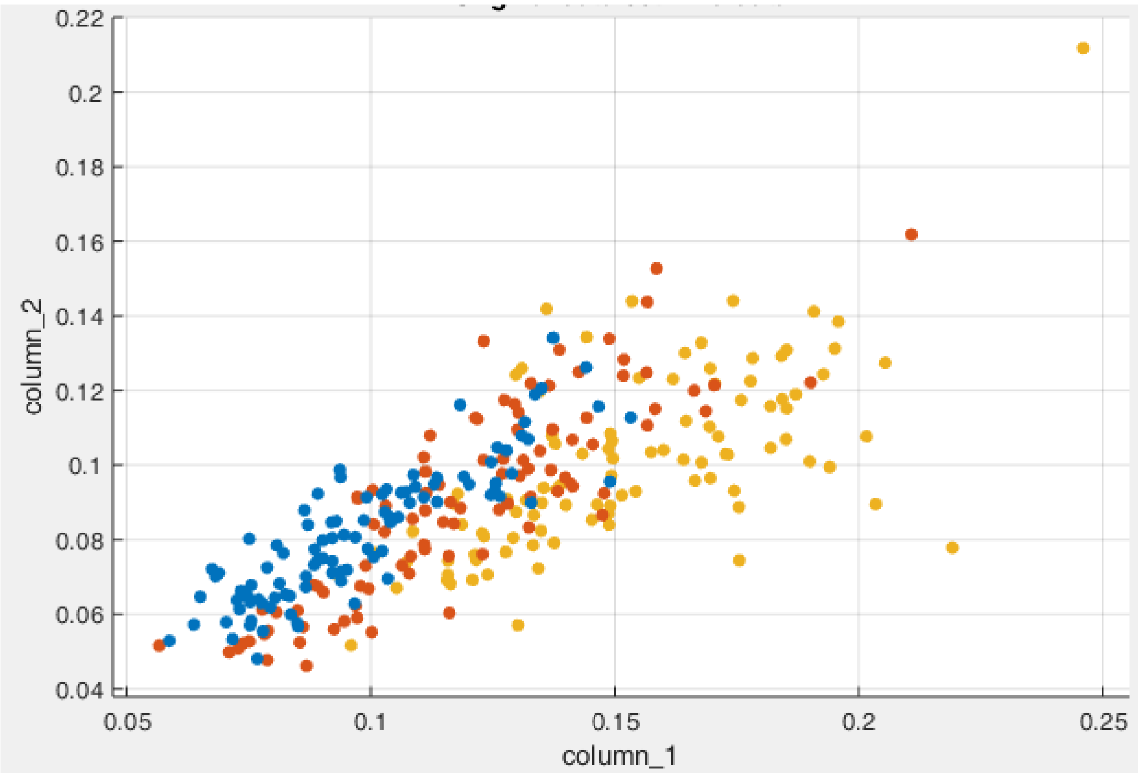

Figure: Scatter plot of Histogram of Oriented Gradients Features (Cell size =32x32).

Tabel2. Results with HoG Features for Script Based Handwritten Document Classification

Classifier	Accuracy with HOG (64x64)	Accuracy with HOG (32x32)
SVM Cubic	98.30%	98.00%
SVM Linear	97.70%	97.70%
SVM Quadratic	98.30%	98.00%
KNN	97.30%	97.70%
LDA	99.00%	93.00%

From Table 2, it is evident that Linear Discriminant Analysis (LDA) outperformed other classifiers, achieving an accuracy of 99.00% with HoG and cell size of 64x64, and 93% with cell size of 32x32. Cubic SVM and Quadratic SVM yielded identical results for both cell sizes, obtaining accuracies of 98.30% and 98.00%, respectively. Linear SVM achieved an accuracy of 97.70% for both cell sizes. Similarly, K-Nearest Neighbors (KNN) demonstrated performance comparable to SVM, with an accuracy of 97.30% for cell size 64x64 and 97.70% for cell size 32x32.

In the figure, a visual comparison of results is provided for ULBP, HoG with cell size 64x64, and HoG with cell size 32x32. The figure clearly shows that ULBP exhibits the best performance across all classifiers. Among the two HoG cell sizes, HoG with 64x64 performed better than HoG with 32x32.

Considering the classifiers, both Cubic SVM and LDA show promise as suitable choices for future research due to their solid performance.

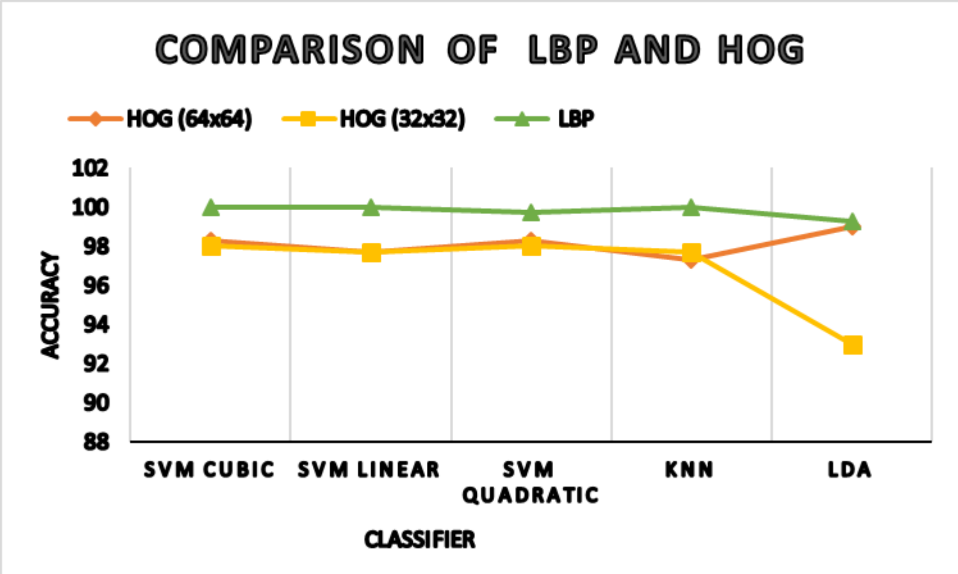

Figure: Comparison between ULBP and HOG for Script based handwritten document classification

We also conducted a comparative analysis of our work with similar studies reported in the literature. In [8], the authors presented a scheme for script identification in handwritten documents, utilizing a symbolic analysis framework. They employed a fusion-based approach, considering Gabor filters, LBP Variance, and Wavelet-based features, resulting in a 123-dimensional feature vector. Their evaluation was performed on a private dataset comprising 300 pages, achieving an average accuracy of 96.60% for script identification.

In comparison to [8], our method demonstrated superior performance, achieving a 3.4% higher accuracy. More recently, authors in [9] presented a similar approach using structural and directional morphology-based features for script identification at the page level, focusing on Indian handwritten scripts. Their method utilized a 144-dimensional feature vector. However, their approach had drawbacks, as it considered structural properties that were sensitive to scale and rotation effects. Additionally, the use of mathematical morphology made their method prone to noise and skew in document images. They reported an accuracy of 95.65% for the combination of Kannada, Devanagari, and Roman scripts.

In contrast, our method outperformed [9], achieving an accuracy that was 4.35% higher than the reported accuracy. Notably, our method demonstrated invariance to noise and rotation, offering promising potential for further improvement when dealing with more complex datasets.

Overall, our comparative analysis highlights that our method exhibits better performance when compared to previously reported methods. Additionally, the inherent noise and rotation invariance of our approach further enhances its potential for handling complex datasets.

Table3. Comparison with earlier work

Ref.	Feature Extraction Method	Script Combination	Dataset Size	Accuracy for Page Level Script Identification
D S Guru et. al. 2013 [8]	Gabor+LBPV+Wavelet [Features Set Size: 123]	Kannada, Devanagari, Roman	**300 Pages** 100 Handwritten Pages Per Script	96.6%
Sk Md Obaidullah et.al. 2017 [9]	Structural and Directional Features Based on Morphology [Features set size: 144]	Kannada, Devanagari, Roman	**378 Pages** Kannada 46 pages, Devanagari 220 pages andRoman 112 pages	95.65%
Proposed Method	**Uniform Local Binary Patterns [Features Set Size: 59]**	**Kannada, Devanagari, Roman**	**300 Pages 100 Handwritten Pages Per Script**	**100%**

Based on our exhaustive experiments and findings from the literature, we have identified several crucial issues in the field of handwritten script identification, which we present below for the benefit of the Document Image Analysis (DIA) community:

1. Evaluation and Benchmarking with Old, Noisy, and Historical Documents:

There is a pressing need to evaluate and benchmark handwritten script identification methods with a broader range of documents, including old, noisy, and historical ones. Dealing with such diverse and challenging datasets will enable a more comprehensive understanding of the performance and limitations of existing techniques.

2. Improving Classification Accuracy with Limited Training Data:

Addressing the challenge of limited training data, especially in the case of low resource languages or sensitive sources, is essential. Mechanisms for improving classification accuracy under these constraints need to be developed to enhance the applicability of handwritten script identification methods in real-world scenarios.

3. Algorithm Development for Both Printed and Handwritten Document Types:

Current script identification approaches often focus on either printed or handwritten document types separately. There is a need to develop algorithms capable of simultaneously dealing with both types of documents, thereby improving versatility and practicality.

4. Creation of Benchmark Public Handwritten Datasets for Indian Scripts:

To foster research and development in the field, it is imperative to create benchmark public handwritten datasets specifically tailored to Indian scripts. Such datasets will facilitate standardization, comparison, and collaboration among researchers, promoting advancements in script identification methods.

5. Handling Smartphone-Captured Heterogeneous Documents:

With the increasing prevalence of smartphones in daily life, a future trend in research involves processing smartphone-captured heterogeneous documents. Developing methods to handle the unique challenges posed by such documents will be pivotal in adapting handwritten script identification to evolving technological landscapes.

By addressing these issues, the DIA community can collectively advance the state-of-the-art in handwritten script identification, making significant contributions to various applications and real-world scenarios.

Conclusion

This paper introduces a novel approach for script-based handwritten document classification, leveraging the effectiveness of Uniform Local Binary Patterns (ULBP) and Histogram of Oriented Gradients (HoG) as efficient texture description methods. Our method offers several advantages, as it does not necessitate segmentation, skew correction, or filtering, streamlining the classification process. Additionally, our approach automatically extracts features without extensive parameter tuning.

The utilization of ULBP features ensures robustness and efficiency in handling the unconstrained nature of handwritten documents. Furthermore, our method demonstrates scalability to rotation invariance and noise immunity, enhancing its adaptability to diverse document conditions.

Through extensive experimentation with our curated dataset, we have observed encouraging performance results compared to state-of-the-art methods. Our approach showcases promising potential for script-based handwritten document classification and offers valuable contributions to the field.

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