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Original Article

Preserving Cultural Heritage: Mapping of Handwritten Modi Script to Devanagari Characters

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***Abstract** - The preservation of cultural heritage through the digitization of historical scripts stands as a testament to the fusion of technology and legacy. This research delves into the development of an automated system that reduces the gap between the ancient Modi script and contemporary digitalization, specifically the conversion from handwritten Modi script to Devanagari script. By leveraging advanced machine learning techniques, a character recognition model capable of interpreting diverse handwritten Modi script styles was engineered. Subsequently, a conversion algorithm was implemented to translate recognized Modi characters into the standardized Devanagari script accurately. The methodology involved meticulous data collection, training, and testing of the recognition model. Results showcase the system's efficacy in accurately recognizing and converting Modi script characters into their Devanagari counterparts across various handwriting styles and complexities. The importance of current work is its contribution to the preservation and accessibility of cultural artifacts, enabling the digitization of historical manuscripts and documents. This work not only offers a technological solution but also serves as a pathway for the conservation and revival of the rich cultural heritage embedded within the Modi script.*

***Keywords** - Devanagari script, Handwritten character recognition, Modi Script, Optical character recognition.*

1. Introduction

The convergence of historical scripts with modern digital technology epitomizes a critical endeavour in preserving and revitalizing cultural heritage. Preservation requires a deliberate and systematic effort to safeguard and maintain cultural, historical, or linguistic artifacts, ensuring their survival for future generations. This involves activities such as documentation, conservation, and digitization, with the overarching goal of preventing the loss or deterioration of valuable elements that constitute a society's heritage. Handwritten documents especially serve as tangible representations of linguistic and cultural evolution, embodying the unique identity and historical journey of the communities that utilized this script. The imperative for preservation arises from the fragility of cultural heritage in the face of time, environmental factors, and evolving communication technologies. Handwritten scripts, especially those like Modi, face the risk of fading into obscurity due to the lack of standardization, limited understanding, and the challenges presented by various natural and human-induced threats. Preserving a script is an endeavor to safeguard the rich tapestry of cultural diversity and linguistic heritage that contributes to the identity of communities. Among these scripts the Modi script [12] is a historical script that predominantly forms the basis of Marathi and Gujarati languages as it stands as a venerable relic of India's linguistic past. Its intricate characters, handwritten over centuries, present a unique challenge in their transition to the digital realm. This research embarks on the journey to bridge this transition by proposing an automated system for the conversion of handwritten Modi script to the widely used Devanagari script.

The essence of this endeavor lies in the symbiosis of technological innovation and cultural preservation. Leveraging cutting-edge machine learning techniques, the research focuses on developing a robust character recognition system capable of deciphering the nuances and variations inherent in handwritten Modi script. Beyond mere recognition, the subsequent translation into the standardized Devanagari script poses an intriguing challenge, entailing a nuanced understanding of linguistic conventions and character mappings.

Through meticulous data collection, model training, and algorithmic development, this research strives to facilitate the preservation and accessibility of historical manuscripts and documents inscribed in Modi script. By automating the conversion process, this work aims not only to bridge the digital divide between past and present but also to facilitate a renewed appreciation and study of India's linguistic and cultural heritage embedded within the intricacies of the Modi script. Many efforts have been made to preserve the Modi script on its own, and this methodology aims to preserve it by digitizing its characters into the well-known Devnagari script. This approach has been largely unexplored.

2. Background

Languages and scripts are integral components of a community's identity, shaping its culture, history, and social fabric. However, many languages and scripts around the world face the threat of extinction due to various factors, such as globalization, urbanization, political changes, and the dominance of major languages. As these smaller languages and scripts decline, there is a risk of losing not only linguistic diversity but also the wealth of knowledge, traditions, and cultural expressions they encapsulate.

To address the urgent need for the documentation and preservation of endangered languages, UNESCO (United Nations Educational, Scientific and Cultural Organization) has created the "Atlas of the World's Languages in Danger." [19] This comprehensive resource categorizes endangered languages into different levels based on their vitality and the degree of endangerment based on the following nine factors:

- The transmission of language across generations
- the overall number of speakers
- percentage of speakers among the world's population
- Language use in established contexts and domains
- Language use in new contexts and media
- Accessibility of resources for literacy and language education
- Language policies of the government and institutional bodies
- Attitudes of the community toward their language
- Quantity and caliber of documentation

This serves as a vital tool for linguists, researchers, and policymakers, offering insights into the global linguistic landscape and providing a foundation for targeted preservation initiatives. Based on the above factors, the categories of classification are as follows:

- Vulnerable (VU): Languages in this category are still spoken by all generations but face a risk of becoming endangered due to external factors.
- Definitely Endangered (DE): These languages are mostly spoken by old people, and they are no longer being passed down to younger generations.
- Severely Endangered (SE): Languages in this category have very few speakers, often limited to the older generation, and are at risk of becoming extinct soon.
- Critically Endangered (CR): These languages have very few remaining speakers, are often confined to a single community, and are on the verge of extinction.
- Extinct (EX): Languages that no longer have any living speakers. However, documentation efforts may exist to preserve knowledge about them.

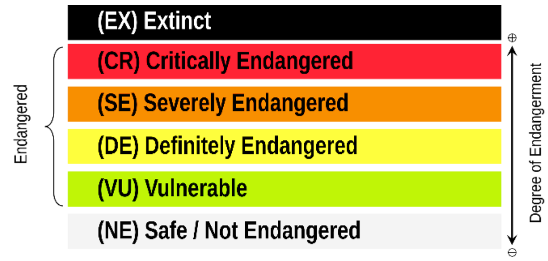

Fig. 1 UNESCO's Atlas of the World's Languages in Danger classification

Table 1. Endangered languages

Language	Status	Comments
Kurukh language	VU	Primarily spoken in Jharkhand, Bihar, Chhattisgarh, and Odisha and written in Kurukh Banna alphabet and Tolong Siki alphabet.
Toda language	CR	Spoken by people in the Nilgiri Hills of Tamil Nadu and has its own alphabet
Gangte language	DE	Spoken primarily in Manipur and written in Meitei script
Aiton language	SE	Spoken primarily in the Dhonsiri Valley, Assam and written using the Burmese script

India, being a linguistically diverse country, is home to numerous languages, some of which face varying degrees of endangerment. Some select few have been mentioned above.

The preservation of older scripts, such as the Modi script, holds multifaceted advantages that extend beyond mere linguistic and historical considerations. Firstly, these scripts serve as invaluable repositories of cultural identity and heritage, encapsulating the linguistic nuances, artistic expressions, and societal norms of bygone eras. Learning and preserving older scripts provide a direct connection to the roots of a community, fostering a sense of cultural continuity and reinforcing a collective identity. Moreover, older scripts often contain a wealth of knowledge embedded within historical manuscripts, literature, and documents. Unlocking the secrets encoded in these scripts can unveil insights into the intellectual, scientific, and artistic accomplishments of past civilizations. This, in turn, facilitates a more comprehensive understanding of human development and contributes to the enrichment of contemporary knowledge.

Additionally, the study and preservation of older scripts contribute to linguistic diversity by safeguarding languages that may be endangered or have evolved. This linguistic diversity is crucial for maintaining a global tapestry of communication and understanding. Through the preservation of older scripts, this not only honor the linguistic diversity of our ancestors but also promotes a richer understanding of the linguistic evolution that has shaped present-day languages. Furthermore, learning older scripts fosters a unique cognitive engagement, enhancing critical thinking skills and providing a distinctive perspective on the evolution of written communication. This cognitive exercise contributes to intellectual flexibility and a broader appreciation for the diverse forms of human expression. In the context of the Modi script OCR research, the need to preserve older scripts is underscored by the desire to ensure the accessibility and digitization of historical manuscripts, safeguarding them from deterioration and loss. Bridging the gap between ancient scripts and contemporary technology not only preserves cultural heritage but also makes it accessible for future generations, fostering a continuum of knowledge and appreciation for the rich tapestry of human history.

3. Research Objectives

The primary goal of this study is to create a specialized system for recognizing handwritten characters utilizing a neural network methodology. Additional aims are:

1. To develop a comprehensive optical character recognition (OCR) system for the transcription of handwritten Modi script into Devanagari script.
2. To innovate linguistic analysis and mapping Strategy for aligning Modi script characters with Their Devanagari equivalents.

4. Theoretical Background

The advent of Optical Character Recognition (OCR) technology and its application in handwriting recognition has been a significant area of research in the field of computer vision and artificial intelligence [20-26]. This field is concerned with the development of computer applications capable of identifying and interpreting handwritten characters from various mediums and converting them into a digital or machine-readable format. Such systems are adept at processing handwriting from physical documents via optical scanning or employing intelligent character recognition techniques. Moreover, they are engineered to recognize pen-tip movements on digital surfaces, capturing the nuances of handwritten input.

4.1. Machine Learning

Machine Learning (ML) represents a sophisticated branch of artificial intelligence that focuses on the development of algorithms and statistical models that enable computers to perform specific tasks without explicit instructions, relying instead on patterns and inferences derived from data. [27] This technology draws upon principles from both psychologies, for its emphasis on learning patterns, and biology, for its inspiration from neural processes, to equip machines with the capability to learn and make decisions from data. A typical application of machine learning in the field of handwriting recognition involves training a model on a dataset of handwritten digits, where each image is tagged with the corresponding digit label. The model, through a process of feature extraction, pattern recognition, and optimization, learns to identify the handwritten digits. [28] It adjusts its parameters to minimize the difference between its predictions and the actual labels, refining its ability to recognize handwritten characters from images accurately.

4.2. Artificial Neural Network

Artificial Neural Networks (ANNs) represent a computational framework modeled on the neural structures of biological brains. [19] These computational networks are structured to emulate the way organic neural networks process information, albeit they do not replicate the intricate biological mechanisms in full detail. ANNs consist of a densely interconnected set of nodes, or artificial neurons, each designed to perform parallel computations for data processing and pattern recognition tasks. [20] Like biological neural systems, ANNs are engineered with the flexibility to adjust and learn from data inputs through a method known as training. This training phase is critical for tailoring the ANN to specific applications, ranging from pattern and anomaly detection to complex character and speech recognition. The learning mechanism within ANNs involves iterative adjustments to the synaptic weights of the connections between neurons based on the discrepancies between actual and desired outputs. The architecture of an ANN is composed of layers that include an input layer, one or more hidden layers, and an output layer. [21] Each neuron within these layers processes incoming data through activation functions, which are mathematical equations that determine whether a neuron should be activated or not based on the input it receives. This setup allows ANNs to capture non-linear relationships within the data. [22] The strength of ANNs lies in their ability to discern patterns within vast datasets, making them exceptionally suited for applications where traditional algorithms struggle to perform. By leveraging gradient-based optimization techniques, such as backpropagation, ANNs can efficiently minimize error rates and enhance predictive accuracy. The distributed nature of computation across neurons and the network's ability to learn from examples contribute to the robustness and scalability of ANNs in handling diverse computational tasks. [23]

4.3. Neural Network Approaches in Handwriting Recognition

The exploration of neural networks, particularly in the application of Optical Character Recognition (OCR) for the preservation of cultural heritage, forms a cornerstone of contemporary computational linguistics and digital humanities. Neural networks, inspired by the biological neural networks that constitute animal brains, operate on a principle where layers of nodes (or "neurons") process information received from preceding layers. This cascading flow of information allows for complex computational processes akin to the way biological neurons transmit signals across the neural network to facilitate cognitive functions.

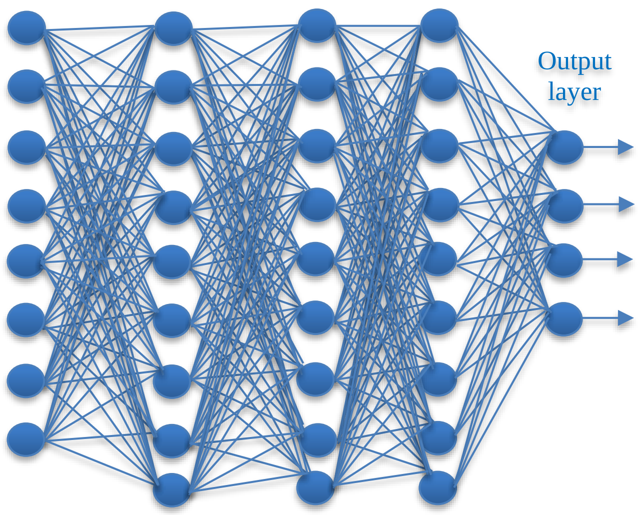

Fig. 2 Deep neural network

In the realm of neural network-based systems, each layer of units receives values from its predecessor, enabling the computation of inputs to yield desired outputs [24]. This process mirrors the biological transmission of signals in the brain, where values traverse from one unit to another within the artificial neural network, culminating in the computation and generation of a new output value [25]. The architecture encompasses layers designated for input and output, with intervening layers known as the hidden layers. These hidden layers constitute the "depth" of neural networks, hence the term "deep neural networks," which are pivotal in processing the values introduced at the input layer. [26]

Figure 2 illustrates this concept, highlighting the integral role of deep neural networks in handwriting character recognition systems. Such systems leverage deep learning to discern characters from handwritten images, a task that underscores the network's ability to learn and recognize complex patterns [27]. The efficacy of a deep neural network in performing functions traditionally associated with neural networks is contingent upon its depth—i.e., the number of hidden layers it possesses. While a more profound network with numerous hidden layers can theoretically model more complex functions, a smaller, well-structured network often achieves computational efficiency without compromising performance [28].

In the context of digitizing and preserving cultural texts, such as the Modi script, the application of deep neural networks in OCR technology presents a promising avenue. This approach not only facilitates the transcription of ancient scripts into digital formats but also contributes to the broader objectives of cultural heritage preservation. By enabling the accurate digitization of historical texts, neural network-based OCR systems ensure that these cultural artifacts remain accessible for future generations, thereby safeguarding the linguistic and cultural diversity they represent.

4.4. Optical Character Recognition (OCR) Technology

OCR technology encompasses a series of processes designed to recognize text within a digital image. It involves several steps, including pre-processing, text detection, character segmentation, recognition, and post-processing. The pre-processing phase aims to enhance image quality, making it more conducive for text detection through techniques such as grayscale conversion, noise reduction, normalization, and binarization. Character segmentation then isolates individual characters for analysis, a critical step for accurate recognition.

4.5. Linguistic Analysis and Script Mapping

For scripts rich in cultural heritage, such as the Modi script, linguistic analysis and mapping to a contemporary script like Devanagari are essential. This process involves a meticulous examination of phonetic, structural, and contextual similarities between the scripts. Establishing a correspondence between characters of both scripts through a systematic mapping table is crucial for the OCR system's ability to recognize and transcribe ancient texts accurately. This not only aids in the digitization and preservation of historical documents but also ensures their accessibility to a wider audience.

Table 2. Summary of Related Research

Ref. No.	Script Recognized	Procedure followed. ML/DL/OCR	Future Work
2	Handwritten MODI script	ML (Support Vector Machine)	Improve recognition rate
3	Devanagari and MODI script	Neural and non-neural network approach	Vowel recognition separately/ recognition rate
4	English	ML (Naïve Bayes algorithm)	Dictionary addition and get more clear images
5	MODI lipi	Neural network (DCNN)	Recognition accuracy, Feature analysis
6	Devanagari	ML/DL (Decision trees, Random Forest)	Preprocessing techniques
7	MODI script	DL (CNN)	Script Segmentation
8	MODI script	Neural network	Character recognition rate and applicable in other languages
9	MODI script	Neural network	Functionality of deep learning
10	English numerical	DL/ML (HWR, HTR, CNN)	Digit recognition

5. Related Work

Preservation of cultural heritage through digitization and preservation of historical texts is a multifaceted challenge that has attracted attention from various studies. Efforts to bridge the transition from handwriting to digital characters have been explored in both linguistic and technological contexts. This section reviews relevant works in the field, discussing methodologies, challenges, and outcomes. The Modi script, an ancient Indian script, has garnered attention in the domain of Optical Character Recognition (OCR) due to its historical significance and the need for digitizing ancient texts. This review aims to analyze and synthesize the methodologies and findings of several research papers focused on recognizing handwritten Modi characters using various ML and DL techniques. Sachdeva and Mittal [6] emphasized machine learning for recognizing compound Modi characters, exhibiting the potential for recognizing complex character structures. Joseph and George [7] utilized advanced convolution based Neural Networks (CNNs) for extracting features within Modi script.

The research demonstrated the efficacy of CNN-based techniques. Furthermore, Anam and Gupta [8] used the Otsu's-Binarization algorithm and Kohonen Neural Networks to recognize Modi Lipi, showcasing the diversity of methods explored in this domain. Mahajan and Tajne [9] contributed to the field by employing deep learning algorithms for recognizing ancient Indian handwritten scripts, shedding light on the applicability of modern techniques to ancient scripts. In contrast, the work of Dixit Kushwah and Pashine [10] delved into recognizing handwritten digits using both machine learning and deep learning techniques, although not directly related to Modi script recognition, highlighting the broader scope of OCR research beyond specific scripts. While these studies vary in methodologies, they collectively emphasize the utilization of ML, DL, extraction of features, and neural networks to address the challenge of recognizing handwritten Modi characters. However, the absence of a unified benchmark dataset and performance metrics across these studies impedes direct comparison and benchmarking of different approaches. In conclusion, the research landscape of OCR for Modi script recognition is evolving, showcasing diverse methodologies and innovative approaches. Future endeavours should emphasize the standardization of datasets, comparative evaluations, and perhaps collaboration to establish a benchmark for evaluating the performance of different OCR techniques on Modi script recognition.

6. Implementation

Our implementation process seamlessly integrated Optical Character Recognition (OCR) techniques and Python programming to transmute handwritten Modi script into the widely accessible Devanagari script. Beginning with the collection of diverse handwritten Modi-script documents, our methodology encompassed high-resolution scanning and image enhancement to optimize input.

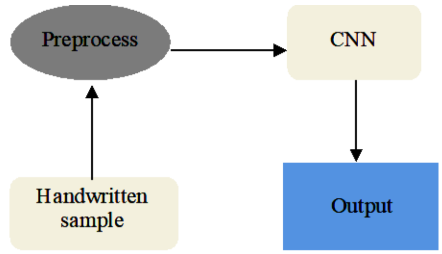

Fig. 3 System design

6.1. System Architecture

This segment outlines the structure and design of the envisioned system for recognizing handwritten characters, which employs a neural network methodology. The system is structured into three main components: input pre-processing, Convolutional Neural Networks (CNN), and the output module.

6.2. Pre-Processing

6.2.1. Grayscale conversion [15]

The image is grayscale once it has been transferred from its original analogue format to a digital one. The information that contained color details has been deleted from the picture. The several shades of grey, where white is the lightest and black is the deepest. Typically, the brightness of its intermediate tones is equal to that of the main hues.

6.2.2. Denoise [16]

By eliminating any tiny spots or patches that are more intense than the surrounding region, the noise reduction step seeks to improve the image's smoothness. It is possible to minimize the noise in both color and grayscale images.

6.2.3. Normalizing [17]

Normalization aims to provide scale consistency for aspect and ratio. It makes it possible to differentiate between various character lengths while classifying. The scaled (normalized) characters will be used for all filter operations. Using a big normalization size will lengthen the training duration of the OCR filter. However, if the size is too tiny, important character details will be omitted.

6.2.4. Binarization [18]

Binarization is the process of converting an image to black and white. Binarization is a trustworthy and efficient method for eliminating text or any other required visual element from the background. The lighting in the picture varies from time to time. Otsu's binarization is useful in this situation. This method uses all the image's attributes to determine a threshold for the entire picture. Image thresholding is automated using this approach. In this instance, it produces a single intensity threshold that separates pixels into classes for the foreground and background. To determine this threshold, it is necessary to either minimize the intra-class intensity variance or maximize the inter-class variation.

6.2.5. Erosion

A structural element is frequently used in the eroding technique to examine and reduce the shapes in the input image. Precision erosion is used to decrease the width of the Modi script characters and increase their separation from one another since they are so closely spaced. Functions mapping an Euclidean space or matrix E into R ∩ {∞, -∞} are called images in monochromatic morphology. An element is represented by ∞ if it is larger than any real number and -∞ if it is smaller than any real number. R is the real number set.

6.2.6. Character Segmentation

Each character is divided into several artifact-based fragments for use in mapping, and various characters linked by image artifacts are kept apart. Segmentation is the process of breaking an image up into smaller pieces for additional processing.

6.3. Mapping Modi Script to Devanagari

The process of mapping Modi script characters to Devanagari involves a meticulous linguistic analysis to establish correspondence between the characters of both scripts. This mapping is crucial for enabling Optical Character Recognition (OCR) systems to accurately recognize and transcribe Modi script into Devanagari, facilitating digital preservation and accessibility of ancient texts.

6.3.1. Linguistic Analysis

The initial phase involved a comprehensive linguistic analysis to identify phonetic, structural, and contextual similarities between Modi and Devanagari characters. Linguistic experts were consulted to discern the underlying phonetic relationships and historical connections between the scripts. This analysis aimed to align characters based on their shared sounds, shapes, and linguistic origins.

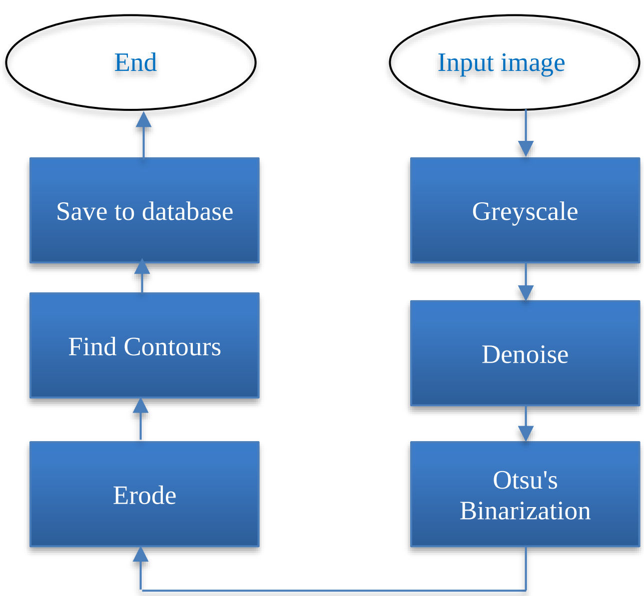

Fig. 4 Pre-processing flowchart

6.3.2. Character Correspondence

Based on the linguistic analysis, a systematic mapping table was developed to establish correspondence between Modi script characters and their Devanagari counterparts. This mapping ensured a structured alignment of characters, enabling a one-to-one or one-to-many relationship between the scripts.

6.3.3. Consonants

For instance, characters such as "Ka" in Modi script were identified to correspond directly to "Ka" in Devanagari, aligning characters with similar phonetic and visual representations.

6.3.4. Vowels and Ligatures

Additionally, the mapping included the recognition of vowels and ligatures, accounting for complex character structures present in both scripts.

6.3.5. Mapping Table Illustration

The culmination of this mapping effort resulted in a comprehensive table illustrating the correspondences between Modi script characters and their Devanagari equivalents. This table, organized systematically, serves as a reference guide for accurate character recognition and conversion in OCR systems. The successful establishment of a structured mapping between Modi and Devanagari scripts lays the foundation for enhanced digitization, preservation, and accessibility of ancient texts inscribed in the Modi script.

Fig. 5 Modi script mapping

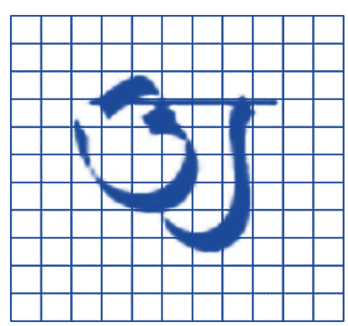

Fig. 6 Single modi character

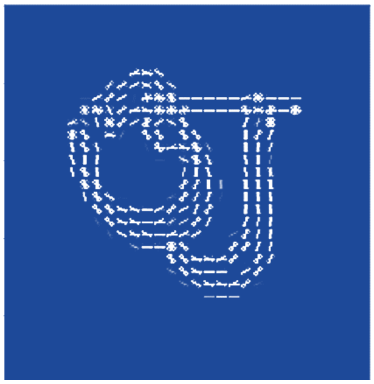

Fig. 7 HOG representation of modi character

6.4. Character Storage

To be able to translate Modi script characters, we need a way of representing them; since these characters are not part of the Unicode standard, they can be represented as vectors. The character image can be flattened into a vector where each element represents the intensity value of a pixel. A 20 x 20 px grid for each character. The resulting vector shall have 400 pixels. This representation, as shown in Figure 7, can then be used to create a Histogram of Oriented Gradient representation. The images can be represented in the form of a Histogram of Oriented Gradients (HOG). It captures the shape and structure of an object or a region in an image by calculating the distribution of intensity gradients. HOG starts by calculating the gradient for each pixel in the image. Gradients represent the changes in intensity or color between neighbouring pixels. From the gradients, two pieces of information are obtained: magnitude and orientation. The magnitude represents the strength of the gradient (how fast the intensity changes). The orientation represents the direction of the gradient the angle of the intensity change. To store this information, a NoSQL database called MongoDB could be used. The database collection contains all Devanagari alphabets as its keys, and the 3D vector of HOG features as its values. Using MongoDB ensures an organized repository for image representation. This approach not only allows for the convenient storage of information but also enables easy querying and comparison of HOG features between different handwritten styles. By structuring the database in this manner, it becomes feasible to perform diverse operations, such as similarity analysis, classification, and recognition of Modi characters based on their HOG representation.

7. Conclusion

The paper presents a deliberate approach aimed at establishing a clear map, essentially resulting in an organized framework for future research efforts. This approach is a guiding principle, providing a structured approach to creating datasets specifically designed for the Modi script. The structured approach outlined in the paper sets a precedent for future endeavours in similar domains or for other scripts and languages. It also serves as a template that researchers can adapt and apply to establish systematic mappings for different scripts, therefore contributing to a broader framework for linguistic and script-based research methodologies.

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