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Research Article

Detection of Gujarati Handwritten Characters using Artificial Intelligence Techniques: Challenges, Opportunities, and Future Directions

Mehulkumar Dalwadi[1], Dr. Abhishek Mehta[2]
[1]*Faculty of Information Technology and Computer Science, Parul University Vadodara, Gujarat*
[2] *Faculty of Information Technology and Computer Science, Parul University Vadodara, Gujarat*

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ABSTRACT

The handwritten character recognition (HCR) has grown significance in document digitisation, multilingual text processing, and automated form interpretation. Among the different Indic scripts it is relatively underexplored, despite a large population of speakers. This paper provides a comprehensive review of the state of the art of Artificial Intelligence (AI) models for the detection and recognition of characters from Gujarati handwritten text. We critically review over 30 work references focusing on the benefits and limitations of traditional machine learning (ML) methods, hybrid models and state-of-the-art deep learning (DL) architectures. We study the unique features of the Gujarati Script including diacritical marks and visually similar subset of characters and their impact on identification quotient. In addition, we discuss important challenges such as the lack of large-scale public datasets, variations in handwriting styles, and the details of Gujarati ligatures. By synthesising current knowledge, identifying methodological gaps, and providing potential future directions, this paper aims to assist both novices and experienced researchers in designing robust, efficient, and scalable solutions for Gujarati HCR.

Keywords: Gujarati handwritten character recognition, handwritten text recognition, artificial intelligence, deep learning, transfer learning, dataset, variability, linguistic complexity.

INTRODUCTION

HCR (Handwritten Character Recognition) is an indispensable domain in the broad context of document digitisation and automated text processing. The importance of this is especially evident in sectors such as education, administration, finance, and archiving etc, where large volumes of handwritten documents need to be converted into a format that can be processed by machine[1]. HCR allows institutions to streamline data entry, protect archive records, and improve language-oriented analytics, consequently advancing research in a variety of global scripts. And although there has been considerable work in languages like English, Arabic, and Devanagari, what little exists in the way of research for Gujarati handwriting is still in the early stages of development, with Gujarati being one of the most popular spoken languages in India[2].

In particular, Gujarati HCR has a level of complexity that is rarely matched by its more straightforward relatives. Several consonants, vowels, diacritical markings, conjunct symbols, and numbers compose Gujarati, and they may be represented in more than one way, sometimes leading downward similar looking glyphs [3]. Additionally, the script quite often require stacking or merging of diacritical marks on each other that, thus need to render the sub-character ranging for complex variety of combinations. Such complexity can increase the likelihood of potential misclassifications, especially in inaccurate scanning environments or fast, cursive handwriting. As a result high performing systems, even state-of-the-art HCR systems, may have difficulty maintaining high accuracy without considerable customisation, data augmentation, or complex computational techniques such as hybridised machine learning or deep convolutional neural networks [4].

Despite these challenges, in the last 10 years, there has been a noticeable increase in the amount of research available on Gujarati HCR, predominantly due to advancements in the field of Artificial Intelligence (AI). Early approaches were based on feature-engineered models, using handcrafted descriptors and classical classifiers like support vector machines or k-nearest neighbours. With the increase in processing power and the availability of large datasets, the focus shifted over time to data-driven approaches such as deep learning. Convolutional neural networks (CNNs), transfer learning, and more recently hybrid architectures have shown promise efficaciously capturing complex attributes of Gujarati script [5]. However, publicly available, large-scale datasets are still scarce, presenting a major challenge for wider benchmarking and standardisation between different research groups [3].

Moreover, the application of these algorithms in real-world scenarios also showed more difficulties, such as handling imbalanced or noisy documents, adapting to domain-centric vocabularies, and operating within resource-limited environments like mobile phones. Thus, although deep learning has demonstrated its power, developers also need to consider efficiency, explainability, and cross-lingual applicability, which still face infancy in the context of Gujarati HCR. Figure 1: A conceptual representation of the intricate nature of Gujarati script and the numerous forms and diacritical placements to make these challenging to automatic systems for identification.

Ans. Figure 1 illustrates the different components of Gujarati handwriting, which includes independent consonants or vowels as well as complex conjuncts. The figure illustrates a typical pipeline for the AI-based procedure, starting with data collection and preprocessing, followed by feature extraction or end-to-end deep learning, and finishing with classification and post-processing. This graphic depicts necessary bottlenecks and decision points with an emphasis on how ostensibly minor differences in character, especially diacritical markings, deeply impact accuracy in reliable identification.

This review attempts to aggregate the existing literature on Gujarati HCR in addition to robustly evaluating its fields of advances, limitations, and ongoing challenges. Section 2 systematically reviews the key papers in this field and describes the evolutionary path we took from classical machine learning to recent deep learning. AI approaches are further elaborated in Section 3, while the challenges posed by Gujarati script are highlighted there. In Section 4, we will outline persisting limitations from the aspect of data and character similarity, setting the observation for Section 5's final discussion on future efforts towards robust, scalable Gujarati HCR approaches.

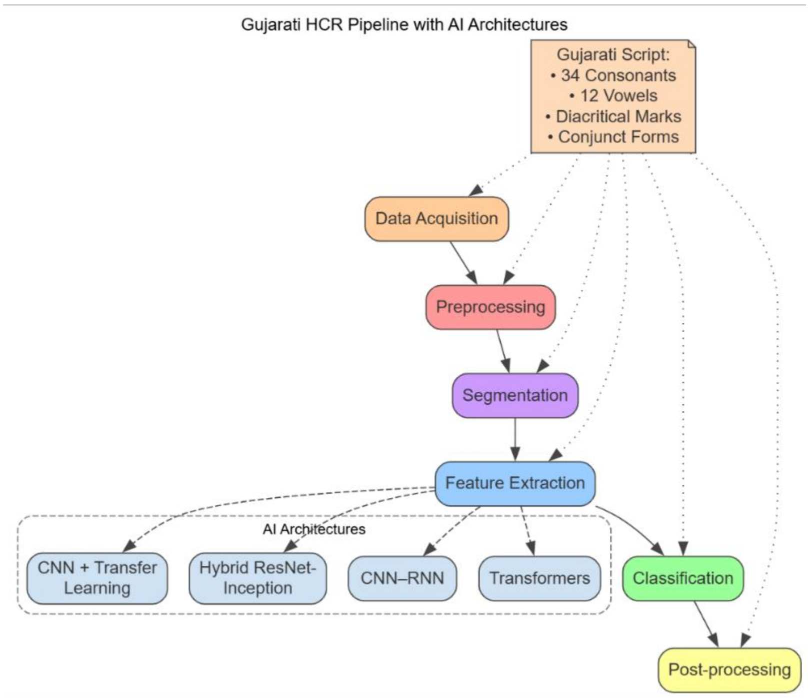

Figure 1 A schematic example of Gujarati script variations and an AI-based workflow

LITERATURE SURVEY

The evolution of Gujarati HCR has progressed from heuristic-based systems to sophisticated neural networks. This section rigorously assesses the principal research in the domain, addressing their methodological advancements and intrinsic limits.

2.1 Early Works: Rule-Based and Classic ML Approaches

Early work on Gujarati HCR mainly relied on rule-based segmentation and manual feature engineering [1][6]. Pareek et al. (2020) developed an offline recognition system, which retrieved geometric as well as stroke-based features to train SVM classifiers. This method achieved a reasonable accuracy level but was limited by needing trained specialists for the subject and being ill-equipped to deal with different handwriting styles.

Sharma et al. (2019) proposed a structural decomposition based approach to manage complex Gujarati characters. They analytically broke down complex ligatures to sub-character parts, allowing for a broad spectrum of categorisation less ambiguity. However, these systems do require thorough pre-processing pipelines and found significant challenges with extremely cursive or warped handwriting.

Naik and Desai (2019) proposed a 3-layer classification technique for online Gujarati handwritten character recognition, combining a stratified heuristic segmentation with a final classification module. However, while showing improved accuracy when compared to single-layer classifiers, the approach's dependence on finely tuned segmentation thresholds limited its generalizability. Standardised datasets were lacking, and thus hinders a cross-comparison with alternative methodologies [7].

While these classical machine learning techniques laid an important foundation, they struggled with large amounts of uncertain data. Given that they were heavily reliant on human feature engineering and optimising for each dataset, their robustness was limited [8]. In Table 1, we provide a summary of several landmark publications and their main findings and limitations.

Table 1: Early ML-Based Works in Gujarati HCR

Study	Approach	Key Insights	Limitations
Pareek et al. (2020)	Hand-engineered features + SVM	Showed feasibility of SVM for Gujarati HCR	Needed extensive feature crafting, limited dataset
Sharma et al. (2019)	Structural decomposition	Better handling of compound characters	Underperformed on cursive/irregular handwriting
Naik and Desai (2019)	Multi-layer online classification	Incremental improvements in digit/character recognition	Highly segmentation-dependent, not standardized datasets
Kathiriya and Goswami (2019)	Rule-based preprocessing + feature design	Provided a baseline for Gujarati text recognition tasks	Narrow coverage of glyph variations, more a conceptual review

(Sources: Sharma et al. 2019; Naik and Desai 2019; Pareek et al. 2020; Kathiriya and Goswami 2019.)

2.2 Transition to Hybrid Frameworks and Ensemble Methods

With the advancement of computer resources, researchers combined several machine learning techniques, occasionally with deep learning models, to enhance accuracy. Doshi and Vanjara (2021) executed an extensive review including classification algorithms including k-NN, SVM, neural networks, and ensemble techniques, indicating that hybrid methods frequently surpassed pure rule-based approaches. They further underscored the incorporation of text modifiers, which are prevalent in Gujarati literature.

Doshi and Vanjara (2022a) presented a hybrid methodology that integrates machine learning classifiers with a CNN-based feature extractor. This pipeline improved identification accuracy by integrating manually designed form descriptors with automatically acquired convolutional features. Despite their promise, the assessments predominantly relied on a restricted, privately sourced dataset, which impedes replication [9]. Doshi and Vanjara (2022b) also emphasised techniques for optimising picture datasets for handwritten Gujarati characters; yet, the absence of extensive, open-source datasets continued to be a considerable constraint.

Another significant contribution is by Suthar and Thakkar (2022), who introduced a hybrid deep ResNet integrated with an Inception module specifically designed for Gujarati optical character recognition. By integrating these two robust CNN architectures, they demonstrated cutting-edge accuracy. The authors observed that their model necessitated substantial processing resources and may not be suitable for real-time applications.

2.3 Emergence of Deep Learning for Gujarati HCR

Researchers introduced CNNs solely based models after the initiation of CNNs in visual image identification tasks. Sorathiya (2021) proposed a CNN design on the Gujarati characters and used data augmentation techniques such as rotation, shifting, zooming to minimize overfitting. The resulting model outperformed classical machine learning benchmarks but the training algorithm was highly dependent on GPU for best performance.

Goel and Ganatra (2023) demonstrated that the use of transfer learning on large datasets (for example, ImageNet) with deep convolutional neural networks greatly increases accuracy on handwritten Gujarati numbers. Building on their work, they laid the groundwork for using pre-trained models to address the data scarcity issue in Gujarati HCR. Staff developers tended to focus heavily on numbers, which lead to a shallow exploration of consonants, vowels and conjunct places.

Limbachiya et al. (2022; 2023) used transfer learning with CNN achieving acceptably high accuracies for alphanumeric Gujarati text. They designed their approach that utilized common CNN layers alongside domain knowledge-based methods such as morphological filters, to handle script-specific issues. While promising, those studies predominantly relied upon alphanumeric characters, and the exploration of complex ligatures was limited.

2.4 Advanced Architectures: ResNet, Inception, and Transformers

Deep learning techniques have made this task easier and more challenging at the same time, where they had to compete with each other to improve accuracy [7], exceeding basic CNNs. Suthar and Thakkar (2022) used Inception modules combined with skip connections of ResNet to extract the multi-scaled features of Gujarati characters. This multi-faceted approach allowed us to model complex stroke-level details alongside the overall structural trends.

Despite the growing use of attention-based architectures for linguistic tasks (including BERT, GPT), the use of such approaches for Gujarati HCR is limited. In (2022), the authors explored CNN-RNN hybrids for Indic handwriting and hinted that the sequential behavior of LSTM or Bi-LSTM may better retain the context & flow of handwritten text. While Devanagari and other scripts have greatly benefited from this process, empirical studies on Gujarati scripts using transformers or recurrent networks are rare [10].

2.5 Critical Observations and Gaps

Despite the great strides, huge gaps remain. Many studies do rely on private or limited datasets, making a fair assessment of techniques difficult [3][4]. The data quality is heterogeneous, with some teams using only synthetic images, while others collect real-world samples that may not be representative of the actual handwriting styles [11][12]. Also, most solutions do not cover all subsets of the Gujarati script (e.g., only digits or only base letters) and not complete text transformation. Such a modular approach enables experimentation, yet does not allow us to fully appreciate the complexity of the whole [9].

Table 2 gives a comparative overview of selected studies, highlighting important methodology, datasets, and achievements, as well as evaluations of their limitations.

Table 2: Comparative Summary of Select Gujarati HCR Studies

Study	Methodology	Dataset Details	Achievements	Critical Review
Doshi and Vanjara (2021, 2022a, 2022b)	Hybrid ML (SVM, k-NN) + CNN feature extractor	Private dataset (~2k samples)	Provided an overview of ML approaches; proposed data optimization	Lack of large public datasets; limited repeatability; text modifiers partially addressed
Sorathiya (2021)	Custom CNN + Data Augmentation	~10k handwritten character images	Showed improved accuracy vs. classical ML	Needs GPU resources; dataset still relatively small
Limbachiya et al. (2022, 2023)	Transfer learning + CNN (alphanumeric focus)	Private alphanumeric dataset (~15k samples)	Achieved high accuracy for digits and letters	Does not extend to modifiers or conjuncts

Goel and Ganatra (2023)	Deep CNN + Transfer learning for numerals	Small numeral dataset (~3k samples)	Demonstrated viability of transfer learning for Gujarati numerals	Focus restricted to numerals; limited exploration of large-scale text
Suthar and Thakkar (2022, 2024)	Hybrid Deep ResNet-Inception + dataset gen.	Custom dataset (size not publicly specified)	State-of-the-art accuracy in pilot tests	Resource-intensive approach, no standard public dataset
Parikh and Desai (2023)	Structural analysis for conjuncts	Focus on conjunct forms, ~2k images	Addressed complexities of conjunct segmentation	Limited coverage of numerals and modifiers
Gongidi (2022)	CNN–RNN for multiple Indic scripts	Various script datasets, partial Gujarati coverage	Proposed synergy of CNN for features, RNN for sequence modeling	Gujarati results not thoroughly validated; emphasis on multi-script

(Sources: Doshi and Vanjara 2021, 2022a, 2022b; Sorathiya 2021; Limbachiya et al. 2022, 2023; Goel and Ganatra 2023; Suthar and Thakkar 2022, 2024; Parikh and Desai 2023; Gongidi 2022.)

ARTIFICIAL INTELLIGENCE TECHNIQUES FOR GUJARATI HANDWRITTEN CHARACTER RECOGNITION

Artificial Intelligence (AI) is essential for tackling the intricacies of Gujarati Handwritten Character Recognition (HCR). Researchers have utilised progressively advanced techniques, from early machine learning (ML) approaches to modern deep learning (DL) methods, to address the script's unique characteristics and stylistic changes. This section offers a succinct summary of Gujarati HCR, starting with the language's distinctive features, progressing through the essential phases of HCR pipelines, and culminating with significant AI designs.

3.1 Gujarati Script and Its Unique Characteristics

The Gujarati script, closely associated with Devanagari, has certain characteristics that necessitate specialised HCR techniques. In contrast to Devanagari, it lacks a top horizontal bar, which may facilitate segmentation while simultaneously presenting other difficulties. Specifically:

- Letter Inventory: Gujarati has 34 consonants, 12 vowels and 10 numbers with various glyphs, all of which can be modified using diacritical marks [9]
- Diacritical marks (matras): These are added to base letters and can significantly alter the shape of a glyph, requiring robust categorisation algorithms [2].
- Conjunctive Forms: Multiple consonants can combine into ligatures, which makes segmentation and feature extraction extremely difficult [11].

Subtle variations in strokes can distinguish unique characters, particularly when matras intersect or create compound glyphs. This morphological intricacy highlights the necessity for sophisticated AI-driven systems that can discern small visual distinctions.

3.2 Gujarati Handwritten Character Recognition (HCR)

A typical Gujarati HCR system follows a multi-step pipeline:

- Data Collection and Pre-processing: Images of handwritten text are obtained through the scanners or digital cameras [13], leading to the photos that can be different in quality. In preprocessing, there are frequently binarization (Otsu's thresholding) and noise reduction (Gaussian blur) which ensure that the input to the next stages are uniform [14]. Some investigations use morphological procedures to tackle difficult backgrounds or overlapping glyphs [15].
- Segmentation may occur at various levels, including word, character, or sub-character level, particularly in conjunct forms. Correct segmentation is critical since errors propagate during classification [16]. Complex diacritical arrangements require careful boundary identification to differentiate multiple elements of individual glyphs [17].

- Feature Extraction or Automatic Feature Learning: Traditional Handwritten Character Recognition (HCR) relied on manually crafted features, such as Gabor filters and histograms of oriented gradients (HOG)[18]. However, current deep learning architectures perform feature extraction internally within their layers, learning edge, curve and diacritical position hierarchies without supervision [18].
- Classification and Post-processing: Classification is based on machine learning methods (e.g. support vector machines, k-nearest neighbours), or deep learning layers (e.g. convolutional neural network softmax output). In the final stage, dictionary searches and language specifications can correct false positive classifications, especially in case of ligatures or handwritten scripts [19].

This process has demonstrated efficacy in several Gujarati HCR systems; nevertheless, real-world implementations frequently encounter limitations such as insufficient training data, noisy surroundings, and the script's intrinsic visual intricacy.

3.3 Illustrative AI Architectures

1. CNN and Transfer Learning: Other works use transfer learning: they train architectures like ResNet or VGG on Gujarati letters [3]. This approach has lower data requirements, but uses generic features trained on large datasets such as ImageNet. But if stream visuals (e.g. the nature sceneries) differ widely upon scanned text, considerable domain readjustment may be required.
2. Hybrid ResNet-Inception: The combination of ResNet skip connections with Inception multi-branch convolutions greatly enhance feature extraction capabilities [14]. Deep layers capture coarse-grained accentenate subtleties while multi-scale convolutions extract global and localized patterns. While hybrid networks show good performance, they can be computationally heavy, warranting work in model pruning or quantisation for faster inference.
3. CNN–RNN (Seq2Seq): CNN–RNN hybrids have shown promise in scripts with cursive or complicated characters [20]. The CNN extracts local features in a frame by frame manner, while an RNN (LSTM or GRU) handles sequence modelling, this is useful when characters are related or edges are fuzzy. While Devanagari has produced a lot of literature, a full study of Gujarati, especially in the large domain of conjunct, is yet to be done[10].
4. Attention Based Transformers: Transformers, which have found great success in natural language processing use, are now increasingly deployed in computer vision for modelling global context, avoiding the sequential restrictions of recurrent neural networks [7]. However, for Gujarati HCR they would offer advanced techniques for focusing on diacritical notches that are placed around a main glyph. The unavailability of sufficient comprehensive Gujarati handwriting corpus is a major challenge for proper training of large transformer architecture models.

The building blocks, benefits, and common caveats of four advanced AI architectures found in Gujarati HCR systems are compared in Figure 2. This conceptual diagram differs from a linear pipeline in that each method is grouped in its own cluster, representing the different ways in which researchers might choose a single approach, or hybridize multiple ones to resolve the script’s diacritical complexities, data limitations, and performance objectives.

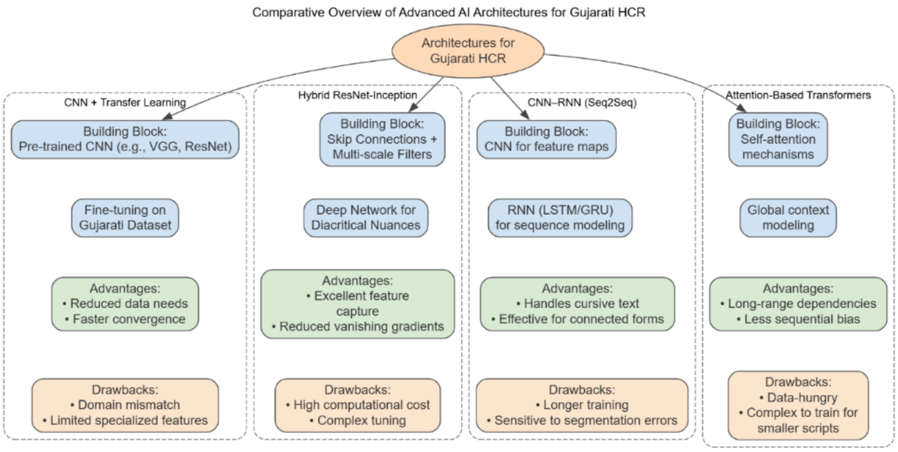

Figure 2 Comparative Overview of Advanced AI Architectures for Gujarati HCR

By using these strategies with comprehensive preprocessing and segmentation procedures, researchers enhance their likelihood of properly interpreting and categorising Gujarati handwritten text. Nonetheless, issues include insufficient data, significant script variability, and substantial processing requirements persist, underscoring the necessity for further innovation in AI-driven solutions for Gujarati HCR.

CHALLENGES AND RESEARCH GAP

Despite promising strides, Gujarati HCR still contends with notable challenges that hinder its wider applicability. These issues underscore the need for continued research, particularly in data collection, advanced modeling, and real-world implementation.

4.1 Variability in Handwriting Styles

Gujarati handwriting may vary significantly according on age, education, area, and individual habits [4]. Data augmentation strategies address this diversity to some extent, however they seldom encompass the complete range of real-world styles [21]. Moreover, a same character may be represented differently by the same person under diverse circumstances, prompting questions over model generalisability [22].

4.2 Similarities Between Characters

The Gujarati script consists of several characters that vary by subtle strokes [23]. For example, "ખ" (kha) and "છ" (cha) may seem misleadingly analogous when inscribed in a cursive style. Minor diacritical errors may result in misdiagnosis [24]. Accurate models therefore require highly discriminative feature extraction techniques.

4.3 Limited Availability of Large-Scale, Publicly Available Datasets

A prevalent motif in Gujarati HCR literature is the deficiency of standardised, comprehensive datasets [3]. The bulk of research depend on proprietary data of limited scale. Furthermore, annotation techniques differ significantly, complicating cross-study comparisons [25]. Table 3 provides a comprehensive comparison of dataset properties in significant Gujarati HCR research.

Table 3: Overview of Dataset Availability in Gujarati HCR

Study	Dataset Size	Data Type	Availability	Notes
Doshi & Vanjara (2021, 2022a, 2022b)	~2k–4k images	Offline handwritings	Private (not public)	Focus on modifiers and base characters
Sorathiya (2021)	~10k images	Characters	Partially shared?	Custom data collection, not widely adopted
Limbachiya et al. (2022, 2023)	~15k–20k alphanumeric images	Mixed	Private dataset	Emphasis on digits and letters
Goel & Ganatra (2023)	~3k numerals	Numerals	Not publicly shared	Transfer learning for numeral recognition
Suthar & Thakkar (2022, 2024)	Not explicitly stated	Characters/numerals	Private (lab-based)	Focus on advanced CNN architectures
Parikh & Desai (2023)	~2k conjunct forms	Conjunct characters	Not publicly shared	Specialized dataset for conjunct analysis
Gongidi (2022)	Varied multi-script sets	Indic scripts	Partial public sets	Generic usage, minimal Gujarati coverage

(Sources: Doshi and Vanjara 2021, 2022a, 2022b, 2024; Sorathiya 2021; Limbachiya et al. 2022, 2023; Goel and Ganatra 2023; Suthar and Thakkar 2022, 2024; Parikh and Desai 2023; Gongidi 2022.)

4.4 Complexity of Gujarati Script

The script's intricacy stems from its extensive character set, many diacritical markings, and conjunct ligatures [26]. Compound characters can significantly modify the fundamental form, while the inclusion of modifiers in various places (top, bottom, side) introduces further diversity [24]. Furthermore, each combination must be precisely identified—an arduous endeavour for both machine learning and deep learning systems.

4.5 Key Research Points

1. From Holistic Word-Level or Sentence-Level Recognition: Most modern approaches focus on single letters or characters. However, in real applications, continuous text recognition is often necessary by contextually informed corrections [19].
2. Real-time or Online Recognition: The most common technique used in modern research is Offline HCR. Few studies exist into tools for interactive writing in the digital space or micro-records oriented toward stylus-based recognition for Gujarati[27].
3. Cross-Language and Transfer Learning: In many respects, Gujarati is similar to other Indic scripts like the Devanagari. However, cross-lingual models and multi-task learning approaches are still underexplored [7].
4. Explainable AI : With the increase of deep models the work on interpreting and explaining models is still in its infancy. However, in sensitive areas, systems transparency is important [19].

Resource-Efficient Architectures: High-end GPUs speed up training and inference but are not viable options in resource-constrained situations. E.g. employing efficient or quantised models can facilitate Gujarati HCR on mobile or embedded devices [12].

CONCLUSION AND FUTURE WORK

This paper has conducted a comprehensive review of published and unpublished work done on Gujarati HWCR. We observed the development of the field, from conventional feature-engineering approaches to complex deep learning frameworks, including CNNs and hybrid ResNet–Inception architectures. Despite significant progress over the past few years, especially regarding transfer learning approaches and data augmentation techniques, various inherent limitations remain prevalent in the state of the art.

A significant barrier is the relative inaccessibility of public databases. Though a few studies yield desirable accuracy metrics, discrepancies in data collection strategies, annotation definitions, and dataset sizes make it difficult to draw comparisons. A focused effort to create and distribute large, annotated handwritten Gujarati datasets may drive new progress in this area.

Second, the script is a complex one requiring sophisticated models with the capability to accurately model diacritical marks, conjunct ligatures, and visually similar character pairs. While methods using multi-scale convolutional filters (as in Inception modules) or sequence modelling networks (LSTM, GRU, or transformers) have been convincing solutions, they have not been systematically carried out in Gujarati HCR. Research into attention based or transformer architecture may allow modeling of letter shapes in context and reduce the chance of misclassification.

This is one of many such examples where laboratory implementation is far ahead of practical frameworks for implementation, echoing the stark difference between bench successes and real world efficacy. However, there is growing demand for easy to use systems that can transcribe natural handwriting directly to digital in near real-time, especially on mobile or resource-constrained platforms. Work on model compression, knowledge distillation, and GPU-agnostic methods may help democratize these systems.

In conclusion, cross-lingual and multi-task learning are huge new areas that have yet to be explored comprehensively. Gujarati might thus gain from its structural similarity to some of the scripts used in other Indic languages (for instance, Devanagari) and hence it can benefit greatly in terms of the transfer learning or multilingual recognition frameworks which will end up improving performance for low resource languages. Adding interpretability modules to these pipelines may help build trust, which can contribute to their wider adoption in sensitive areas like government, finance, and healthcare.

Future Directions

1. Dataset Standardisation: Dipe people generate large scale public datasets of Gujarati handwriting covering different age groups, writing instruments, and scanning conditions.
2. Advanced Architectures: Implementation and extensive analysis of transformer inspired architectures and CNN-RNN hybrids for word level processing and line level processing.
3. Real-Time Systems: Study of systems that use resources efficiently and may employ pruning, quantisation or edge computing frameworks in order to achieve real-time recognition.

4. Explainable HCR: Utilizing attention visualisation methods, like Grad-CAM, to identify errors and improve model transparency.
5. Data ScarcityMitigating Cross-Lingual transfer using cursive and behenic alignment of representation learning between Gujarati and other Indic scripts to attain precision in recognition.

By addressing research gaps in a systematic way, academic and industry organizations can augment the reliability and accuracy of Gujarati HCR systems. The open-sourcing of modern AI frameworks, in conjunction with growing data availability, allows Gujarati to be used in some applications, from automated form filling to the preservation of old manuscripts. This will ensure that Gujarati is an important part of the multilingual computing of the future.

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