IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 5, Issue 6, April 2025

Impact Factor: 7.67

Review on MODI Script Character Recognition Using Deep Learning Techniques

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Abstract: *The MODI script, a historic Indian script with limited use in administrative activities from the 17th to 19th centuries, is highly challenging for character recognition systems. The MODI script characters are dissimilar, have intricate structures, and exist with different handwriting patterns, hence rendering automatic identification cumbersome. Despite the limitations, some machine learning, especially deep learning, methods have been utilized to recognize MODI scripts accurately in recent years. This review investigates the uses of convolutional neural networks (CNNs), transfer learning models such as VGG16 and ResNet, and mixed architectures fusing CNN with Support Vector Machines (SVM). We discuss these methods' methodologies, advantages, and disadvantages, explain challenges concerning dataset insufficiency and handwriting diversity, and propose possible future studies to enhance recognition systems. This article emphasizes the importance of automated MODI script recognition in preserving and making historical documents accessible..*

Keywords: MODI Script Recognition, Deep Learning, Convolutional Neural Networks (CNN), Transfer Learning, Optical Character Recognition (OCR), Historical Document Preservation, Machine Learning, Handwritten Script Recognition, Hybrid Models, Cultural Heritage Accessibility

I. INTRODUCTION

The MODI script, which originated in Maharashtra, India, dominated administrative and official writing from the 17th century to the early 19th century. Characterized by its cursive nature and complex character composition, MODI script is a formidable subject for digital character recognition, particularly in documents of historical origin where manual handwriting permutations and document deterioration compound complexities for automated recognition. Considering the cultural and historical importance of MODI manuscripts, digitization of these manuscripts is important to preserve India's heritage. However, conventional Optical Character Recognition (OCR) systems, which are mainly developed for more popular scripts such as Latin and Devanagari, find it difficult to recognize MODI characters correctly because of their unique shapes and intricate interconnectivity between characters. Applications. The emergence of deep learning has transformed character recognition, providing advanced models with the ability to tackle intricate scripts. Convolutional Neural Networks (CNNs), which use the discovery of spatial relations within images, have proven especially successful in image recognition. By identifying fine-grained characteristics and spatial patterns within characters that traditional OCR engines miss, CNNs demonstrated their superior performance in MODI script identification. For example, CNNs can capture subtle features that enhance precision when recognizing MODI characters with varying stroke overlaps or thicknesses. Apart from CNNs, transfer learning is an effective approach when there is limited training data. Even with small MODI datasets, pre-trained models like VGG16 and ResNet have been trained on huge datasets and can be used to recognize MODI scriptsby leveraging their learned features. This allows deep learning methods to be used more efficiently on niche applications like MODI and reduces the computer resources needed to train models from scratch.

Moreover, hybrid approaches that blend CNNs with traditional machine learning methods, like Support Vector Machines (SVM), have been explored. In such approaches, CNNs are used for feature extraction, and SVM is used for the classification process, thereby providing a more robust solution to the intricate nature of MODI script. These hybrid

DOI: 10.48175/IJARSCT-25318

techniques attempt to integrate the deep learning capability of CNNs with the robust classification performance of SVMs, addressing some of the pitfalls that arise when using stand-alone models.

Despite these developments, MODI script recognition faces various challenges. Initially, the non-availability of labeled MODI datasets limits the training of deep learning models since large datasets are necessary to achieve high accuracy levels. Secondly, inherent handwriting differences between regions and time frames further complicate this. Thirdly, aging over time can degenerate manuscripts into making character detail non-discernible, rendering complex preprocessing programs to restore character legibility.

This paper provides an in-depth overview of existing MODI script character recognition techniques, comparing the merits and drawbacks of various methodologies. We discuss CNN-based models, transfer learning usage, and ensemble models, highlighting their promise to address the specific challenges of MODI script. Moreover, we outline possible future research avenues in MODI script recognition, including synthesizing data to complement limited datasets, applying attention mechanisms for enhanced feature localization, and integrating these systems with IoT frameworks for massive-scale processing of historical texts. By promoting MODI script recognition abilities, this study promotes India's cultural heritage preservation, broadening accessibility and facilitating historical knowledge for future generations.

II. LITERATURE SURVEY

The first Optical Character Recognition (OCR) techniques paved the way for successfully recognizing MODI scripts. Patel et al. [1] were the first to try MODI recognition through template matching, a method where character templates are pre-defined and matched against input characters. This technique resulted in just 65% accuracy since it could not handle the significant variation in writing and the exclusive cursive MODI script writing style that always leads to overlapping characters. Though weak in its execution, this research laid the foundation, emphasizing MODI complexities in recognition and a requirement for more flexible solutions.

Joshi et al. [2] suggested a feature extraction-based method that extracted the strokes and contours unique to MODI characters using edge detection and shape analysis to get over the drawbacks of template matching. Though their approach had a 70% success rate, it could not handle noisy data and damaged manuscripts, as is common in old collections. The results highlighted the need to create algorithms to extract subtle properties without relying on clear-cut, flawless data.

Researchers considered more and more sophisticated models as machine learning gained popularity. Kumar et al. [3] employed a Support Vector Machine (SVM) classifier on well-prepared MODI datasets that improved recognition when coupled with preprocessing techniques such as binarization and morphological processing. While the model's accuracy was 78%, its application was limited to clean and consistent MODI texts. This research advocated for more flexible and trustworthy models while pointing to the prospect of machine learning.

The deep learning turn saw a sea change since Sharma et al. [4] brought Convolutional Neural Networks (CNNs) to MODI recognition. It was found that CNNs, renowned for their ability to identify spatial hierarchies in images automatically, could extract the intricate structure of MODI characters. With an impressive 85% accuracy rate, Sharma's CNN model established a new benchmark for MODI detection. Spurred by this development, Verma et al. [5] utilized features learned from large datasets using transfer learning with a pre-trained VGG16 model. Despite minimal training data, this yielded better accuracy and decreased training time, with 88% on MODI datasets.

Rathod et al. [6] examined ResNet, a deeper CNN model with skip connections for further advancements. The model allowed the network to extract more detailed data without encountering the vanishing gradient problem. This approach enhanced accuracy to approximately 89%, presenting ResNet's capability to process MODI's complicated structures. Subsequently, upon understanding that the cursive shape of MODI creates sequential dependencies within characters, Deshmukh et al. [7] integrated CNNs with Long Short-Term Memory (LSTM) networks. Compared to earlier CNN models, our integrated model enhanced accuracy by 12% without losing spatial and temporal information.

Following Pandey et al. [8] coming up with a CNN-SVM approach where CNNs extracted features and SVMs did classification, hybrid models gained more prominence. The hybrid proved that combining feature extraction with traditional classifiers was possible and could address MODI's complex patterns more accurately, as much as 10%

compared to CNN alone. Utilizing the ensemble feature of Random Forest to enhance recognition strength even more, Singh et al. [9] used a CNN-Random Forest hybrid model, which proved robustness to noisy input.

Small annotated datasets were a recurring problem, and Kulkarni et al. [10] attempted to solve this using Generative Adversarial Networks (GANs) for synthetic data creation. Training GANs on available MODI images generated high-quality, diverse synthetic samples, resulting in a 10% improvement in CNN model performance when paired with real MODI data. Pathak et al. [11] made this process more sophisticated by introducing realistic handwriting variation and degradation effects into their GANs, which allowed models to generalize better and achieve over 90% accuracy.

Attention mechanisms became popular since researchers sought to enhance model concentration on important character areas. Nair et al. [12] used an attention-based CNN model that aimed computational attention on important areas of MODI characters, with state-of-the-art results and above 92% accuracy. Gupta et al. [13] later built on this by combining attention with ResNet, enabling the model to automatically shift focus by special MODI character characteristics, leading to the best accuracy ever witnessed.

In parallel, practical applications emerged with Jain et al. [14], who integrated MODI recognition into IoT platforms to enable real-time digitization. This system facilitated large-scale MODI text processing for cloud-based storage, setting a foundation for accessible digital preservation. Agarwal et al. [15] expanded on this by incorporating edge computing, which allowed efficient MODI recognition even on low-power devices, making real-time processing feasible in remote settings.

To address issues of document degradation, Bhosale et al. [16] introduced preprocessing techniques specifically for faded characters. They applied image improvement, binarization, and thresholding to enhance character visibility, resulting in 15% improved accuracy. Patil et al. [17] continued to develop these techniques, applying noise reduction filters and morphological processing to purify deteriorated manuscripts, resulting in remarkable recognition improvement for historical documents.

Handwriting style inconsistency continued. Through domain adaptation transfer learning, by transferring pre-trained Devanagari models and adapting them to recognize MODI, Rajput et al. [18] developed transfer learning. The experiment's accuracy rate was enhanced by 8%, showing the success that could be attained through cross-script learning. To take it a step further, Vyas et al. [19] developed a multi-task learning model to identify both MODI and Devanagari based on the common characteristics of both scripts to achieve the highest accuracy in both datasets.

To enhance resilience, Kuldeep et al. [20] explored ensemble models that blended CNNs with ResNet and various other architectures. They achieved greater than 92% accuracy using a combination of predictions from several different models, indicating how well ensemble methods cope with MODI's intricate complexities. By assigning a weight to every model's predictions based on correctness, Dhavale et al. [21] further fine-tuned this, enhancing consistency and reliability on challenging MODI texts.

Joshi et al. [22] introduced few-shot learning in low-data conditions, where the model learned MODI characters using very few training examples. Inspired by this research, Mehta et al. [23] introduced meta-learning, enabling the model to learn how to adapt quickly to new handwriting styles, with good performance on unseen characters with little retraining.

Most studies were interested in determining and measuring MPs in environmental samples. Prata et al. (2018) presented a novel hybrid strategy, while Naik et al. [24] integrated CNNs with decision trees, creating a trade-off between accuracy and interpretability. Although highly accurate, this model was simpler to analyze and useful for digitizing historical archives. Shinde et al. [25] concluded this wave of research by developing a language model for post-recognition correction, using MODI grammar rules to reduce errors, significantly enhancing the readability and usability of MODI OCR outputs.

Rajesh et al. [26] further developed a hybrid CNN-BiLSTM model to capture the sequential nature of MODI's cursive style. The Convolutional Neural Network (CNN) component extracted spatial features, while the Bidirectional Long Short-Term Memory (BiLSTM) network learned the character dependencies in the MODI script, resulting in an overall recognition accuracy of 91%. This approach showed the potential of combining spatial and temporal feature extraction to handle MODI’s flowing script better.

ISSN: 2581-9429
Volume 5, Issue 6, April 2025
Impact Factor: 7.67

With a foundation built from feature learning, Choudhury et al. [27] demonstrated unsupervised learning through autoencoders and used it for MODI character recognition when data was unavailable in labeled forms. The autoencoder framework learned simpler character forms and developed a solid basis that was then fine-tuned on a supervised dataset for better recognition rates. Applying unsupervised feature learning for MODI, especially with low data settings, was the central focus of this research.

Patwardhan et al. [28] employed a capsule network (CapsNet) that kept the spatial hierarchies of MODI characters intact since it was a sophisticated cursive script. At 93% accuracy, the model understood the interactions between the numerous strokes within each character owing to capsule networks. This process showed that complex scripts such as MODI maintained spatial relations between different strokes.

Rao et al. [29] explored reinforcement learning to improve feature extraction. In this case, an agent achieved a comparable accuracy rate to deep CNN models by learning to choose the most relevant MODI character features. This reinforcement learning introduced a new method of adapting recognition systems to the specific features of MODI through dynamic control of its attention to character features.

A new way of applying MODI-specific data augmentation methods was proposed by Kulkarni et al. [30], generating variations in stroke thickness, character orientation, and size. The generated synthetic data improved model recognition and generalization by 8% through increased training sets. This paper showed how data diversity can improve MODI recognition performance.

Iyer et al. [31] explored hierarchical classification by employing a hierarchical CNN model to classify MODI characters based on their visual similarities. Initially, clustering similar characters and refining recognition within each cluster yielded outstanding classification accuracy and performed particularly well with MODI's visually heterogeneous characters.

Desai et al. [32] employed graph neural networks (GNNs) to represent MODI characters as graph nodes with structural connections among the strokes of a character. The model captured within-character associations due to the novel approach, which resulted in an interpretable character recognition method with competitive accuracy.

Transformer-based models for MODI script identification were proposed by Bhagat et al. [33], who applied self-attention processes to identify inter-stroke relationships between each character's strokes. The self-attention of the transformer allowed the model to identify nuances correctly, outperforming conventional CNN and LSTM models and boasting the highest MODI recognition accuracy to date.

To improve character segmentation, a character segmentation model was proposed by Pawar et al. [34], which segmented characters within words before their recognition. Pre-processing thus significantly improved model accuracy as individual characters were processed without distraction from surrounding strokes, a common issue in handwritten MODI script.

Even further refining sequence-based recognition, Jadhav et al. [35] deployed a sequence-to-sequence model that continuously permitted MODI text recognition as a sequence of characters. The model performed better at dealing with cursive writing and recorded high recognition rates by processing every line of text as a continuous sequence, incorporating contextual dependencies lost in earlier models.

Investigating other feature extraction methods, Singh et al. [36] used wavelet transforms to extract frequency-based features of MODI characters. With this, and using CNN, there was enhanced character texture handling and higher recognition rates, especially on degraded manuscripts.

Khan et al. [37] utilized a few-shot learning paradigm to overcome the data paucity issue, with the model trained on small quantities of labeled MODI samples. Their method achieved competitive recognition performances and proved that few-shot learning can be a realistic solution for MODI datasets that are typically sparse.

Sharma et al. [38] investigated meta-learning, enabling the model to learn to adapt rapidly to new handwriting styles with little retraining. This model performed well on unseen MODI character samples and is a promising solution for handwriting variations in MODI manuscripts.

To attempt to capture finer features, Ghosh et al. [39] used attention-augmented GANs to produce synthetic MODI data with high-stroke details. The GAN model produced more realistic MODI variations, which promoted training data diversity and the CNN recognition rate when synthetic data was included.

DOI: 10.48175/IJARSCT-25318

Kapoor et al. [40] utilized transfer learning with fine-tuning to their specific domains using models previously pre-trained for Sanskrit and Devanagari to improve recognition of MODI. These models fine-tuned on the data for MODI provided over a 90% improvement in accuracy and revealed cross-lingual promise with transfer learning.

Researchers such as Nanda et al. [41] used residual attention mechanisms todynamically modify model attention over various regions of MODI characters. Being especially useful when dealing with degraded or partially obscured characters, the model achievedan accuracy of 93%, greatly boosting its robustness in real-world applications.

With a focus on historical documents, Patel et al. [42] used image restoration techniques to preprocess MODI documents. Applying denoising filters and contrast enhancemententhanced character legibility, which yielded greater recognition accuracy on old documents.

Through pre-training GANs with fake MODI features and subsequent fine-tuning using real MODI samples, Joshi et al. [43] proved synthetic-to-real adaptability. It provided a general approach to applying synthetic data to improve recognition in the real world.

Deshmukh et al. [44] introduced a multi-modal recognition model that integrated visual and contextual knowledge for MODI detection. With the synchronization of visual recognition with MODI grammar, their hybrid approach attained good accuracy with the help of contextual hints from language models and visual hints from CNNs.

Summary of the Literature Survey

This chapter summarizes the most significant advancements and challenges in microplastic detection science, synthesizing the most crucial findings of recent research. As global microplastic pollution rises, numerous strategies have been employed to enhance detection efficacy and accuracy, from advanced machine learning algorithms to more traditional methods such as microscopy and spectroscopy. Their efficiency, scalability, and limitations for both conventional and AI-based detection methods are discussed in detail in this section

Table 1: Summary of the Literature Survey

Sr No.	YOP	Title and Name of Author	Main Findings	Methodology	Limitation	Application
1	2015	Patel et al.	Template matching achieved 65% accuracy for MODI recognition but struggled with variations.	Template Matching	High misclassification with handwriting variations.	Baseline for MODI recognition techniques.
2	2016	Joshi et al.	Improved accuracy by using feature extraction methods.	Edge Detection and Shape-Based Feature Extraction	Struggled with noisy and degraded data.	Feature analysis of MODI character shapes.
3	2017	Kumar et al.	The SVM classifier achieved 78% accuracy but required consistent, clean data.	Support Vector Machine (SVM) with Preprocessing	Limited performance on varied or degraded documents.	MODI character classification.
4	2018	Sharma et al.	CNNs achieved 85% accuracy by capturing intricate MODI character features.	Convolutional Neural Networks (CNN)	Computationally intensive; needs large training data.	MODI character recognition in digital OCR
5	2018	Verma et al.	Transfer learning with the VGG16 model reached	Transfer Learning with VGG16	Limited by small dataset size for MODI	MODI recognition

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ISSN: 2581-9429

Volume 5, Issue 6, April 2025

Impact Factor: 7.67

			88% accuracy.		script.	with transfer learning.
6	2019	Rathod et al.	ResNet's skip connections improved accuracy to 89%.	ResNet with Skip Connections	Complex model; high computational requirements.	Feature extraction in complex MODI characters.
7	2019	Deshmukh et al.	Combined CNN-LSTM boosted accuracy by 12% on cursive MODI script.	CNN and LSTM Hybrid	Struggles with high variability in handwriting.	Recognition of cursive MODI script.
8	2020	Pandey et al.	CNN-SVM hybrid achieved a 10% accuracy improvement.	CNN for Feature Extraction, SVM for Classification	Computationally intensive for large datasets.	Enhanced feature extraction for MODI script.
9	2020	Singh et al.	CNN-Random Forest hybrid showed robustness on noisy data.	CNN with Random Forest Classifier	Limited by data quality and model complexity.	MODI OCR on noisy and degraded datasets.
10	2021	Kulkarni et al.	GANs for synthetic data generation improved accuracy by 10%.	Generative Adversarial Networks (GANs)	Synthetic data may not fully represent real-world MODI.	Data augmentation for MODI recognition.
11	2021	Pathak et al.	Improved GANs with realistic variations in handwriting.	GANs with Handwriting Variations	Computational complexity in GAN training.	Enhanced data diversity for MODI OCR.
12	2021	Nair et al.	The attention-based CNN model reached over 92% accuracy.	Attention Mechanism in CNN	Needs significant computational resources.	Focused MODI character recognition.
13	2021	Gupta et al.	The attention-basedResNet model achieved the highest accuracy at 93%.	ResNet with Attention Mechanisms	Requires large datasets for training effectiveness.	Improved accuracy in MODI OCR systems.
14	2022	Jain et al.	Real-time MODI digitization with IoT platforms for large-scale applications.	CNN-based MODI Recognition integrated with IoT	Requires a stable network for cloud processing.	Large-scale MODI text digitization.
15	2022	Agarwal et al.	Edge computing enabled MODI recognition on low-power devices.	CNN with Edge Computing	Limited processing power and data limitations.	MODI recognition in remote/low-resource areas.
16	2022	Bhosale et al.	Preprocessing techniques improved faded character readability by 15%.	Image Enhancement and Preprocessing	Limited by the degree of document degradation.	MODI OCR on degraded manuscripts.
17	2022	Patil et al.	Noise reduction filters significantly improved	Noise Reduction Filters,	Limited effect on heavily damaged	Recognition in historical

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			recognition accuracy on historical documents.	Morphological Operations	documents.	MODI archives.
18	2022	Rajput et al.	Transfer learning with domain adaptation improved accuracy by 8% for MODI recognition.	Transfer Learning with Domain Adaptation	Limited by the similarity between MODI and source domains.	MODI and Devanagari cross-recognition.
19	2022	Vyas et al.	Multi-task learning enabled joint MODI-Devanagari recognition, leveraging shared features.	Multi-task Learning Model	High computational requirements; needs related datasets.	Multi-script character recognition.
20	2023	Kuldeep et al.	Ensemble methods with CNN and ResNet achieved over 92% accuracy.	Ensemble Models with CNN and ResNet	High computational cost with multiple models.	Robust MODI recognition on challenging texts.
21	2023	Dhavale et al.	Weighted ensemble models further improved recognition consistency and accuracy.	Weighted Ensemble Techniques	Increased complexity; challenging to interpret.	Consistent MODI OCR on complex datasets.
22	2023	Joshi et al.	Few-shot learning enabled high accuracy with minimal MODI training samples.	Few-Shot Learning	Limited by representation diversity in few-shot samples.	MODI OCR with limited data.
23	2023	Mehta et al.	Meta-learning allowed the model to adapt to new handwriting styles with limited retraining.	Meta-Learning Techniques	Limited to specific types of variation in handwriting.	Dynamic MODI recognition adaptation.
24	2023	Naik et al.	CNN-Decision Tree hybrid model balanced accuracy and interpretability for MODI recognition.	CNN-Decision Tree Hybrid Model	Not optimal for highly complex scripts or noisy data.	MODI recognition in interpretable OCR models.
25	2023	Shinde et al.	Language models reduced misclassification errors, enhancing OCR readability.	Language Models for Post-Recognition Correction	Limited by the language model's accuracy and training data.	Post-processing MODI OCR.
26	2023	Rajesh et al.	CNN-BiLSTM model achieved 91% accuracy on cursive MODI texts by capturing character dependencies.	CNN-BiLSTM Hybrid Model	Computationally intensive; struggles with noisy data.	Recognition of cursive MODI sequences.
27	2023	Choudhury et al.	Unsupervised autoencoder learning enabled feature extraction from unannotated MODI data.	Autoencoders for Unsupervised Feature Learning	Requires labeled data for fine-tuning in recognition tasks.	MODI feature learning for data-scarce scenarios.

28	2023	Patwardhan et al.	Capsule Networks achieved high accuracy by capturing spatial relationships within characters.	Capsule Networks (CapsNet)	High model complexity; challenging for real-time applications.	Hierarchical MODI recognition.
29	2023	Rao et al.	Reinforcement learning agent optimized feature extraction for improved MODI accuracy.	Reinforcement Learning for Feature Optimization	Computationally expensive; requires fine-tuning of parameters.	Adaptive feature extraction in MODI OCR.
30	2023	Kulkarni et al.	Data augmentation techniques increased model robustness and improved accuracy by 8%.	Data Augmentation with Variations	Augmented data may still lack realism for some MODI texts.	MODI data diversity for better generalization.
31	2023	Iyer et al.	Hierarchical CNN grouped MODI characters by visual similarities, improving classification accuracy.	Hierarchical Convolutional Neural Network (CNN)	Model complexity requires initial grouping accuracy.	Grouped MODI character recognition.
32	2023	Desai et al.	Graph Neural Networks (GNNs) captured structural dependencies in MODI characters, enhancing recognition.	Graph Neural Networks (GNNs)	High computational demands; limited generalization on varied datasets.	Structural MODI character analysis.
33	2023	Bhagat et al.	A transformer-based model with self-attention achieved the highest MODI recognition accuracy.	Transformer with Self-Attention	High computational needs; requires extensive training data.	High-accuracy MODI OCR.
34	2023	Pawar et al.	The character segmentation model improved MODI recognition by isolating characters within words.	Character Segmentation Preprocessing	Limited efficacy on highly cursive and overlapping characters.	Enhanced MODI text segmentation.
35	2023	Jadhav et al.	The sequence-to-sequence model improved the recognition of cursive MODI text as a continuous sequence.	Sequence-to-Sequence Model	Limited by data quality in heavily degraded manuscripts.	MODI recognition in continuous cursive scripts.
36	2023	Singh et al.	Wavelet transform with CNN enabled better handling of character textures, improving recognition of degraded manuscripts.	Wavelet Transforms with CNN	Limited computational resources are required for the wavelet transform.	Texture-based MODI recognition on degraded data.
37	2023	Khan et al.	Few-shot learning reached competitive	Few-Shot Learning	Limited by diversity in few-shot learning	MODI recognition

			recognition rates with minimal MODI training samples.		samples.	with minimal data.
38	2023	Sharma et al.	Meta-learning enabled the model to adapt to new handwriting styles, achieving strong results on unseen samples.	Meta-Learning Techniques	Limited by specific handwriting variations in MODI script.	Adaptable MODI character recognition.

III. DISCUSSION

The principal findings of many studies are outlined in the Discussion section of MODI script recognition, which also contrasts the advantages and limitations of various methods and offers suggestions for future research. Though simple, traditional techniques such as template matching and straightforward feature extraction do not generalize due to the inherent randomness of handwritten MODI characters. These techniques are effective in controlled data but have difficulty with degraded manuscripts and inconsistent handwriting styles, making them less effective in real-world applications.

More recent deep learning developments, specifically in hybrid models and Convolutional Neural Networks (CNNs), have demonstrated immense capabilities in automatically classifying MODI character recognition more accurately. Hybrid models can catch the fine details and relationships in MODI script and classify complex characters robustly. With models like VGG16 and ResNet, transfer learning has improved recognition performance by tapping pre-trained expertise from similar scripts, minimizing the data required for MODI-specific training. Yet, such methods need high computational power levels and large amounts of labeled datasets, which may be challenging in real-time, low-power environments.

Attention models and transformer-based models have further pushed the area by facilitating focused recognition and enhancing accuracy in separating MODI characters even from degraded text. Nevertheless, these models are intricate and consume considerable computational power, which can restrict their application in portable or low-resource environments. Hybrid methods combining CNNs with language models for post-processing have enhanced readability and grammatical correctness, highlighting the advantage of combining character recognition with contextual awareness.

Another area of promise is the application of Generative Adversarial Networks (GANs) and few-shot learning-based synthetic data generation to overcome the data scarcity bottleneck, a prevalent bottleneck for MODI recognition. By generating realistic handwritten variations, these approaches can help improve the robustness of recognition models. Nevertheless, synthetic data could fail to reproduce the variability of actual MODI manuscripts, implying that more sophisticated data augmentation methods and domain adaptation should be employed to address different handwriting styles and document quality.

The field applicability of such systems is still an issue since many of these methods are robust in lab settings but fall behind in field conditions where aspects of document degradation, lighting, and ink variation can affect the accuracy. Integrating such systems with IoT platforms for mass-scale digitization would open doors for wider applications. Cost and access are still the major impediments, especially in the case of heritage conservation in resource-poor environments.

Future research must focus on developing portable, real-time, low-cost recognition systems adaptable to varying document conditions. Advances in synthetic data generation and transfer learning can reduce dataset limitations, which promotes generalization between document characteristics and handwriting forms. In addition, the trustworthiness and deployment utility of MODI recognition systems will be enhanced by focusing on model explainability and cross-validation across diverse dialects and domains. This discussion emphasizes the need for a multidisciplinary approach that integrates cutting-edge AI and IoT technology with traditional computational methods to meet the specific challenges of MODI script preservation and recognition.

IV. CONCLUSION AND FUTURE SCOPE

The optical character recognition (OCR) research community and digital preservation of historical documents have taken a keen interest in the MODI script, an ancient and advanced Indian script. This research analyzed the development of MODI identification methods, ranging from template matching to basic feature extraction to the latest fad of deep learning-based models. Despite the traditional approaches providing the basis for MODI OCR, their adoption in mass digitization is restricted because they cannot deal with diverse handwriting, damaged manuscripts, and live environments. On the other hand, deep learning-based methods, such as CNN-based models and hybrid networks, have delivered considerable accuracy enhancement, facilitating automatic, high-speed MODI character recognition in multiple environments. Despite this, some challenges remain to overcome, including the very high computational resources needed, the lack of labeled datasets, and the cursive and complex character structure of MODI. Again, high implementation costs can make it less accessible, particularly to smaller institutions and projects in resource-constrained environments.

Future work in MODI script recognition mustconsiderdesigning hybrid systems that blend deep learning models with language and grammar-based post-processing methods, enhancing accuracy and readability in challenging handwritten texts. Incorporation of transfer learning and synthetic data generation methods could reduce data paucity problems, enabling models to generalize across diverse handwriting styles and deteriorated documents. Moreover, attention-based and transformer models should be explored further to enhance specificity and focus on critical character details, improving recognition accuracy for challenging texts. Developing portable, cost-effective solutions is essential, especially for real-time field applications in historical archives and educational institutions. Future advancements should also include IoT-enabled platforms to facilitate large-scale digitization and remote data collection, allowing for real-time monitoring and analysis of MODI texts. By addressing these challenges, future research can contribute to creating robust, accessible, and highly accurate MODI recognition systems, paving the way for preserving linguistic heritage and fostering further research in historical and cultural studies.

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