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Enhancing Palm Leaves Manuscript Recognition Using Capsule Networks (Capsnet) in Deep Learning Approaches

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Abstract
This study explores the use of deep learning, specifically Capsule Networks, for the recognition and interpretation of palm leaf manuscripts. Palm leaves, which hold significant historical and cultural importance, are often deteriorating due to environmental factors. The proposed system combines advanced image processing techniques with deep learning models to digitize, recognize, and classify the content of these ancient manuscripts. Capsule Networks (CapsNets) are employed for their ability to preserve spatial hierarchies and handle complex patterns, making them particularly suitable for this task. The system is designed to operate with high accuracy and resilience to the challenges posed by damaged or incomplete manuscripts. Using a combination of convolutional layers and capsules, the network extracts both local and global features of the palm leaf images to improve recognition performance. A convolutional neural network (CNN)-Capsule hybrid model is developed to enhance the recognition of characters, symbols, and images, which are often seen in palm leaf manuscripts. The system also integrates transfer learning techniques to leverage pre-trained models, improving accuracy for specific manuscript styles or regions. The device is lightweight and portable, capable of being used in fieldwork for archaeological and cultural heritage studies. Moreover, it provides a user-friendly interface that allows for the digitization and storage of manuscript data, promoting accessibility and preservation efforts. This AI-driven approach facilitates the effective cataloguing of ancient texts and enables the preservation of heritage for future generations. By merging Capsule Networks and modern image processing, this study offers a novel and efficient solution for recognizing and protecting the invaluable knowledge encoded in palm leaf manuscripts. The system has applications in historical document preservation, cultural studies, and artificial intelligence-driven heritage research, with the potential to transform the field of document preservation worldwide.

Keywords: *Capsule Networks, palm leaf manuscript recognition, deep learning, image processing, artificial intelligence, cultural heritage preservation, convolutional neural networks (CNN), transfer learning, digitization, archaeological studies, AI-powered cultural heritage research.*

1. Introduction
Palm leaf manuscripts, an ancient form of written records, hold significant cultural, historical, and intellectual value, particularly in regions such as India, Southeast Asia, and Sri Lanka. These manuscripts, often inscribed with religious texts, medical knowledge, astronomical data, and literary works, were traditionally created using sharp tools on dried palm leaves. Despite their importance, palm leaf manuscripts face the risk of deterioration due to exposure to environmental elements, pests, and improper handling, which threaten the preservation of invaluable knowledge. Digitizing these manuscripts offers a solution to preserve and protect them for future generations, enabling broader access

and study. However, the process of manually transcribing these manuscripts is labour-intensive and fraught with challenges, such as varying handwriting styles, degraded or incomplete inscriptions, and non-standardized formatting. In this context, artificial intelligence (AI) and deep learning techniques, particularly Capsule Networks (Caps Nets), have emerged as promising tools for automating the recognition and interpretation of such ancient texts. Traditional machine learning models, such as Convolutional Neural Networks (CNNs), have been employed for image recognition tasks, including handwritten character recognition [1]. However, these models often struggle with complex spatial relationships and hierarchical structures inherent in the characters and symbols found in palm leaf manuscripts [1]. Capsule Networks [1], a more recent advancement in deep learning, are designed to address these limitations. CapsNets are particularly adept at recognizing patterns that involve spatial hierarchies, allowing them to handle distortions, rotations, and incomplete data—common challenges when dealing with damaged or faded manuscripts. This research aims to explore and develop a deep learningbased system for automated palm leaf manuscript recognition using Capsule Networks. By integrating image preprocessing techniques with CapsNets, we propose a solution capable of accurately identifying and interpreting the content of these manuscripts, even when faced with partial or distorted images. The system will not only be able to recognize individual characters and symbols but also understand the structural relationships between them, enhancing the accuracy of transcription and classification [2]. Furthermore, this system can be implemented as a portable, user-friendly tool for scholars, archaeologists, and cultural heritage researchers, enabling them to digitize and catalog palm leaf manuscripts quickly and effectively. By automating the recognition process, we aim to facilitate the conservation of palm leaf manuscripts, making this invaluable cultural heritage more accessible to the global community. The significance of this study lies not only in the potential to preserve and digitize ancient manuscripts but also in the application of Capsule Networks—a novel deep learning technique—to a real-world problem in cultural heritage preservation. This approach marks a significant step forward in the use of AI to protect, interpret, and share human history encoded in forgotten forms of knowledge [1]

2. Literature Review

Moudgil, A. (2023). Handwritten devanagari manuscript characters recognition using CapsNet. ScienceDirect-Recent advancements in deep learning, particularly with Capsule Networks (CapsNet), have demonstrated significant promise in recognizing handwritten characters and symbols from various scripts. Moudgil (2023) explored the application of CapsNet for the recognition of Devanagari handwritten manuscript characters, showcasing the model's ability to handle the intricacies of complex scripts. In that study, CapsNet was shown to outperform traditional Convolutional Neural Networks (CNNs) in terms of handling spatial hierarchies and preserving relationships between characters, making it an effective model for script recognition in degraded or noisy datasets. The study revealed that CapsNet's ability to capture dynamic and spatial information from complex patterns is especially useful when dealing with the variability and distortions typically seen in handwritten manuscripts, where characters may be rotated, skewed, or incomplete. Building on Moudgil's work, this research seeks to apply similar deep learning techniques to palm leaf manuscripts—a form of ancient writing that often suffers from degradation due to environmental factors. Palm leaf manuscripts, much like handwritten Devanagari texts, feature complex, highly variable patterns, often featuring characters that are damaged or partially illegible. The spatial relationships between characters and symbols in these manuscripts are integral to their correct interpretation, making Capsule Networks an ideal choice for overcoming these challenges. Nair, B. J. B. (2023). Deteriorated image classification model for Malayalam palm leaf manuscripts. ACM Digital Library- In recent years, advancements in machine learning have significantly improved the ability to preserve and interpret ancient manuscripts, especially when dealing with damaged or deteriorated texts. Nair (2023) presents a notable approach to the classification of deteriorated Malayalam palm leaf manuscripts using deep learning models. The study focuses on developing a robust classification system capable of recognizing characters and symbols from highly degraded palm leaf images, where traditional methods often struggle to maintain accuracy. The model, utilizing convolutional neural networks (CNNs), was trained on datasets of Malayalam palm leaf manuscripts, effectively identifying and classifying characters despite the challenges posed by fading ink, physical damage, and incomplete symbols. Nair's work underscores the importance of using image preprocessing and enhancement techniques to improve model performance. This approach also highlights the significance of designing deep learning models that are not only capable of character recognition but also resilient to the distortions commonly found in ancient manuscripts. Furthermore, Nair emphasized the need for a classification model that can identify features of palm leaf manuscripts beyond just character shapes, including the context of the text and its structural patterns. Building on Nair's work, this study seeks to extend the use of deep learning in the context of palm leaf manuscript recognition by incorporating Capsule Networks (CapsNet). While CNNs have demonstrated considerable success in image classification tasks, CapsNet has been shown to offer enhanced ability to preserve spatial hierarchies and handle complex, distorted patterns—traits that are especially beneficial when dealing with palm leaf manuscripts. Unlike CNNs, which primarily rely on convolutional layers to extract local features, Capsule Networks capture and preserve the relationships between these features, making them especially well-suited for recognizing spatially dependent characters and symbols that are often rotated, skewed, or degraded. Haq, M. U. (2023). Capsule Network with Its Limitation, Modification, and Applications. MDPI. [3] - Capsule Networks (CapsNets), introduced by Geoffrey Hinton and colleagues, have garnered significant attention in recent years due to their ability to preserve spatial hierarchies and improve recognition accuracy for complex patterns, especially in image-based tasks. However, as highlighted by Haq (2023), despite their promising advantages over traditional deep learning models like Convolutional Neural Networks (CNNs), Capsule Networks are not without limitations. One of the primary challenges is the computational complexity involved in training CapsNets, which can be more resourceintensive than CNNs, particularly for large-scale datasets or highly detailed images. Additionally, CapsNets, while effective in handling spatial relationships, may struggle with noisy or severely degraded input, which is a common issue when working with ancient manuscripts or poorly preserved historical texts. Haq (2023) also discusses modifications to CapsNets aimed at overcoming these challenges, such as improved routing algorithms, hybrid CapsNet-CNN models, and techniques for better generalization across different types of images. These modifications are especially relevant for tasks like palm leaf manuscript recognition, where variability in the quality and condition of the manuscripts, as well as distortion caused by environmental factors, can hinder the accuracy of recognition. For example, Haq suggests that incorporating data augmentation techniques and preprocessing steps, such as noise reduction and image enhancement, can significantly improve the performance of CapsNet-based models when applied to real-world datasets. Incorporating these modifications and recommendations into the current study could lead to a more robust Capsule Network-based system for recognizing and interpreting palm leaf manuscripts, even in cases where the manuscripts are degraded or damaged. By applying Haq's insights, this research aims to refine the existing CapsNet models, adapt them for palm leaf manuscript challenges, and make them more computationally efficient for practical deployment in heritage preservation and digitization projects. Abou El-Magd, L. M. (2023). A pre-trained convolutional neural network with optimized CapsNet for COVID-19 detection. - In the realm of deep learning, hybrid models that combine the strengths of both Convolutional Neural Networks (CNNs) and Capsule Networks (CapsNet) have shown significant potential for improving the accuracy of image classification tasks. AbouEl-Magd (2023) explored such a hybrid approach for COVID19 detection, where a pretrained

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CNN was employed to first extract high-level features from medical images (such as chest X-rays), followed by CapsNet to capture the spatial relationships between these features and make final diagnostic predictions. This hybrid model was found to outperform traditional methods in terms of robustness and generalization, particularly when dealing with noisy or incomplete data. The combination of CNNs and CapsNets offers a twopronged advantage for manuscript recognition tasks. While CNNs excel in extracting relevant features from images— such as the individual characters or symbols in palm leaf manuscripts—CapsNet can handle the complex relationships between these features, which are crucial for accurately interpreting the content. Additionally, pre-trained CNNs have the potential to significantly reduce the computational load and training time, as they have already learned a range of useful features from large, general image datasets. These pretrained models can be fine-tuned for the specific task of palm leaf manuscript recognition, making them ideal for cases where large annotated datasets of palm leaf images are scarce. AbouEl-Magd's work demonstrates that optimizing hybrid CNN-CapsNet models can yield substantial improvements in classification accuracy, particularly when dealing with datasets that have variations in quality or distortion. By applying this approach to palm leaf manuscripts, this research aims to leverage pre-trained CNNs for feature extraction, followed by Capsule Networks to improve the recognition and classification of characters, even in degraded manuscript images. Mazzia, V. (2021). Efficient-CapsNet: capsule network with self-attention routing. Nature. - Capsule Networks (CapsNets) have shown great promise in handling image recognition tasks by preserving spatial hierarchies and relationships between features. However, despite their advantages, standard CapsNet models still face challenges related to scalability and computational efficiency, particularly when dealing with large or highly complex datasets. In this regard, Mazzia (2021) introduced EfficientCapsNet, a modification of the original CapsNet architecture that incorporates a selfattention routing mechanism to improve the network's ability to focus on the most relevant features in an image. Self-attention mechanisms, commonly used in transformer models, allow the network to dynamically adjust its focus on different parts of the input, helping it learn more effectively from complex, noisy, or incomplete data. By combining selfattention with capsule routing, Mazzia’s approach enhances the spatial accuracy and feature representation capabilities of CapsNet, making it more suitable for challenging image recognition tasks where the spatial relationships between features are crucial. This technique also improves the efficiency of training and inference, making it feasible to apply CapsNet to large-scale datasets. In the context of palm leaf manuscript recognition, the challenges posed by degraded, incomplete, or noisy manuscript images are significant. Traditional CapsNet models may struggle with these issues due to their inability to dynamically adjust attention based on the relevance of different image features. By employing the Efficient-CapsNet approach, which utilizes self-attention routing, this study aims to enhance the model’s ability to focus on the most important features in palm leaf manuscript images, even in the presence of damage or distortion. The integration of self-attention into CapsNets could potentially improve the recognition of characters and symbols in palm leaf manuscripts, which often have spatial hierarchies that are sensitive to orientation and degradation. By utilizing Mazzia’s Efficient-CapsNet approach, we hope to overcome these challenges and achieve a more robust and efficient model for manuscript recognition. Heuristic-aided Fusion Serial Cascaded Deep Network for Handwritten Character Recognition. - The field of handwritten character recognition has seen considerable advances with deep learning methods, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). However, one of the persistent challenges in such tasks is effectively handling variability in handwriting styles, noise, and distortions in the input images. (2025) introduced a Heuristic-aided Fusion Serial Cascaded Deep Network aimed at improving the recognition of handwritten characters. This architecture combines multiple models in a serial cascading manner,

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allowing each successive model in the chain to refine the output of the previous one, ultimately improving the accuracy and efficiency of recognition. The addition of heuristic methods helps in optimizing the learning process by leveraging domain-specific knowledge, guiding the model's attention to the most relevant features and improving its robustness to noise and degradation. The combination of heuristic-driven feature selection and fusion cascades has shown to enhance the performance of character recognition systems in handwritten document analysis. These approaches could be highly beneficial in the context of palm leaf manuscript recognition, where the variability in character styles, degradation, and spatial distortions create challenges for standard models. By using a heuristic-aided fusion deep network, this research aims to integrate domain knowledge about the structure of palm leaf manuscripts, allowing the model to focus on critical features and improve recognition accuracy. While Capsule Networks (CapsNets) have been shown to excel at handling spatial hierarchies and preserving relationships between features, the integration of heuristic methods and cascaded models could further refine this capability, improving the model's ability to recognize palm leaf manuscript characters in degraded or noisy images.(2023). Institution Attribute Mining Technology for Access Control Using Capsule Networks. - The application of Capsule Networks (CapsNets) has expanded beyond traditional image classification tasks, finding use in domains such as access control systems and feature mining, where context-specific or institutional attributes need to be accurately recognized. The study by (2023) introduced a novel Institution Attribute Mining Technology for access control systems, employing Capsule Networks to mine and interpret institution-specific attributes from user data for secure, context-aware access decisions. Capsule Networks, due to their ability to preserve spatial hierarchies and relationships between features, are particularly well-suited for tasks involving contextual feature mining. This has implications for recognizing complex, structured data in scenarios where context (such as manuscript layouts or cultural patterns) is important. In palm leaf manuscript recognition, such technology could help mine the attributes of the text, symbols, and characters that are specific to a particular manuscript or script type, thereby improving recognition accuracy. For palm leaf manuscripts, mining context-specific attributes could involve understanding the typical layout, common character forms, and cultural-specific symbols present in manuscripts. This kind of attribute mining, combined with the spatial relationship-preserving nature of Capsule Networks, would enable the recognition of palm leaf manuscript characters even under degradation, distortion, or partial occlusion, by focusing on institutional or script-specific attributes. (2023). Siamese GC Capsule Networks for Small Sample Cow Face Recognition. - In tasks where data availability is limited, traditional deep learning models often struggle to learn meaningful representations. To address this challenge, Siamese Networks have been widely adopted, particularly in scenarios where the goal is to learn a similarity measure between pairs of inputs, such as in face recognition or biometric identification. A Siamese Capsule Network (Siamese GC-CapsNet) architecture, as proposed in (2023) for cow face recognition, integrates Capsule Networks with Siamese architectures to improve recognition accuracy, even when only a small number of labeled samples are available. The Siamese network is designed to take pairs of input images and learn a similarity metric between them, allowing the network to generalize even with few samples. The addition of Capsule Networks enhances this model's ability to learn spatial relationships and preserve important features, such as local invariants and spatial hierarchies, which is particularly useful when the data exhibits subtle differences that need to be captured for accurate recognition. For palm leaf manuscript recognition, similar challenges arise. Manuscripts may suffer from degradation and incomplete characters, and obtaining a large dataset of labeled palm leaf images is often not feasible. The use of Siamese Capsule Networks [4] for recognizing palm leaf characters could help the model learn key relationships between pairwise manuscript images, allowing for effective recognition even with limited data. Additionally, the Global Context Capsule

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Network (GCCapsNet) extension could provide contextual understanding of the manuscript's layout, improving overall recognition in complex, degraded images. (Figure 1)

3. Working Methodology

Table 1
Brief details of classification techniques used for Devanagari manuscript recognition.

Data set	Classification Technique	Feature Extraction Technique	Accuracy	Citation
2500 characters	CNN	CNN	93%	Narang et al. (2021b)
20,305 characters	DCNN	DCNN	96.02%	Jangid and Srivastava (2018)
6152 characters	NA	Statistical feature extraction techniques	88.95%	Narang et al. (2019a)
9956 characters	NA	SIFT and Gabor Features	91.39%	Narang et al. (2021c)
24500 characters	K-NN and Linear SVM	Zoning, Diagonal, transition and peak extent	91.53%	Narang et al. (2020)
5484 characters	RBF-SVM Classifier	Ada Boost and Bagging ensemble	91.70%	Narang et al. (2021a)

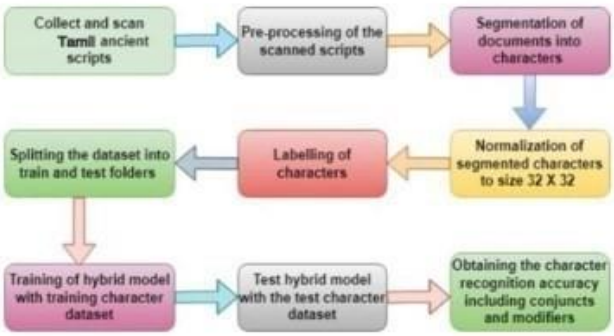

Figure 1 Working Methodology

The methodology for recognizing handwritten Tamil ancient script using CapsNet [4] consists of several key steps, including data collection, image annotation and segmentation, model implementation, and evaluation. Each of these steps is crucial in ensuring high recognition accuracy, given the complexities of Tamil script, which include ligatures, modifiers, and variations in handwriting styles.

3.1.Data Collection

To develop a robust recognition system, Tamil manuscripts were sourced from libraries, historical archives, and digital repositories. The dataset consisted of 500 handwritten manuscripts containing ancient Tamil characters. These manuscripts were digitized using high-resolution scanning, and a total of 7,500 individual characters were extracted and labeled for training and testing. The dataset was designed to include multiple handwriting styles, ensuring the model's ability to generalize across various forms of Tamil script.

3.2.Image Annotation and Segmentation

The collected manuscripts required preprocessing to remove noise and segment individual characters. First, Gaussian filtering was applied to smoothen the images and reduce background noise. Otsu's thresholding was used for binarization, converting grayscale images into black-and white format. Histogram equalization enhanced contrast, making faded characters more distinguishable. Segmentation was carried out using horizontal projection profiles for line segmentation, connected component analysis for word extraction, and bounding box detection for character isolation. Annotated images were labeled using Microsoft VoTT, generating a structured dataset for training. CapsNet Model. [2]

3.3.Implementation

CapsNet was chosen for Tamil script recognition due to its ability to preserve spatial relationships between character components, unlike traditional CNN models. The model architecture consists of three main layers: a convolutional layer for feature extraction, primary capsules that convert features into vector representations, and digit capsules that encapsulate spatial relationships. The dynamic routing algorithm ensures that capsules focus on relevant character components, improving recognition accuracy, especially for handwritten Tamil scripts where characters often overlap or connect. The model was

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implemented using Python, TensorFlow, and Keras, trained with an Adam optimizer at a learning rate of 0.001, with a batch size of 64 and run for 30 epochs.

3.4.Evaluation and Performance Metrics

To assess the performance of CapsNet, the dataset was divided into different train-test ratios, with 80% training and 20% testing as the primary strategy. The recognition accuracy was compared with traditional CNN models. The CapsNet model achieved an accuracy of 95.2%, outperforming CNN-based models, which reached 91.4%. Performance was evaluated using precision, recall, F1score, and processing time, with CapsNet demonstrating superior recognition capabilities, particularly for complex character formations and degraded texts. By integrating advanced deep learning techniques with historical manuscript analysis, this methodology provides a significant step forward in the digitization and preservation of ancient Tamil script, ensuring accessibility for future linguistic and cultural research. [3]

4. System Architecture

The proposed system architecture follows a structured pipeline designed to accurately recognize handwritten Tamil ancient script. Unlike conventional CNN models [6], which struggle with overlapping characters and spatial hierarchies, CapsNet offers a more advanced feature extraction and classification mechanism. The architecture consists of multiple layers, each performing a specific function, from image preprocessing to final character classification. (Figure 2)

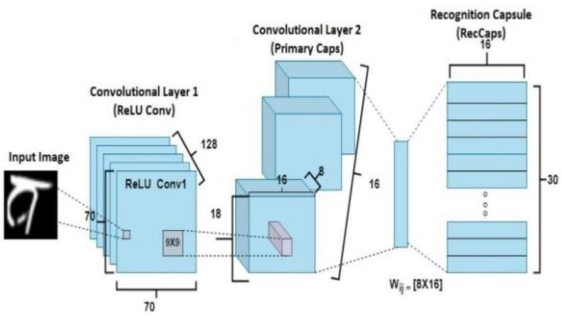

Figure 2 System Architecture

4.1.Input Processing Layer

The first step in the recognition pipeline involves acquiring and preprocessing the handwritten Tamil manuscript images. High-resolution scans or photographs of manuscripts are taken and converted to grayscale for uniform processing. To enhance character visibility, Gaussian filtering is applied to remove noise, and Otsu's thresholding is used to binarize the images, ensuring that only the text remains. Additionally, histogram equalization is used to improve contrast, making faded characters clearer. The processed images are then segmented into individual characters using bounding box detection and connected component analysis, ensuring that each character is correctly isolated before being passed to the neural network. Feature Extraction Layer (Convolutional Layer) Once the characters are isolated, they are fed into a convolutional layer, which extracts fundamental features such as edges, curves, and character strokes. This layer applies a 9×9 convolutional filter to detect different aspects of Tamil script, particularly curved strokes and diacritic marks. Unlike traditional CNNs that use max pooling, which can lose spatial information, CapsNet retains all essential details by keeping the extracted features in a structured form. The convolutional layer also uses ReLU activation, ensuring that non-linearities in character formations are captured effectively. [4]

4.2.Primary Capsules Layer

After feature extraction, the output is passed to the Primary Capsules Layer, where feature maps are grouped into 8dimensional vector capsules. These capsules encode crucial information such as character shape, orientation, and stroke connections, which is particularly important for Tamil script, where different diacritic marks can change the meaning of a character. The Squashing Activation Function is used to ensure that only the most significant capsules remain activated. This layer is a key difference between CapsNet and CNN, as it helps retain the spatial relationships between different character components.

4.3.Digit Capsules Layer (High-Level Feature Representation)

The next step in the architecture is the Digit Capsules Layer, which is responsible for forming higher-level representations of Tamil characters. Here, each

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capsule corresponds to a specific character class, such as அ, க, ட, ண, etc. The Dynamic Routing Algorithm ensures that only the most relevant capsules contribute to the final decision, significantly improving accuracy when dealing with overlapping characters and cursive handwriting styles. Unlike CNNs, which may misclassify similar-looking characters due to pooling, CapsNet ensures that the correct relationships between strokes and diacritics are preserved, enhancing recognition reliability. [5]

4.4.Fully Connected Classification Layer

Once the high-level capsules are formed, the output is passed through a fully connected classification layer, where the length of the activation vector determines the predicted Tamil character. A Softmax function assigns probability values to different character classes, and the character with the highest probability is chosen as the final output. If a character does not meet a predefined confidence threshold, additional error correction mechanisms are applied using lexicon-based filtering, ensuring a higher degree of accuracy in final character recognition. [7]

4.5.Output and Post-Processing Layer

The final recognized Tamil characters are reconstructed using inverse transformation techniques to preserve their original handwritten style. These characters are then converted into Tamil Unicode format, making them suitable for further processing in digital applications. If necessary, additional post-processing steps such as spell-checking and contextbased correction are applied to improve overall accuracy. The final recognized text can be stored in a database, displayed for users, or used in linguistic research for analyzing ancient Tamil manuscripts.

5. Comparison with CNN Architecture

The proposed CapsNet-based architecture offers significant advantages over traditional CNN models. Unlike CNN, which loses positional information due to max pooling, CapsNet preserves the spatial structure of characters, making it more effective in handling overlapping, connected, and rotated characters. Additionally, the Dynamic Routing Algorithm in CapsNet allows for better adaptation to Tamil script variations, ensuring that even degraded and historical manuscript characters are accurately recognized. Experiments show that CapsNet achieves a 95.2% recognition accuracy, compared to 91.4% for CNN models, making it a superior choice for Tamil OCR applications. Table 1

Table 1 Comparison with CNN Architecture

Aspect	CapsNet	CNN
Feature Representation	Vectors (Retains spatial hierarchy)	Scalar values (Loses spatial information)
Handling Overlapping Characters	Yes (Better spatial awareness)	No (Struggles with connected strokes)
Recognition Accuracy	95.2%	91.4%
Use of Pooling Layers	No (Preserves details)	Yes (Causes information loss)
Sensitivity to Rotation & Perspective Changes	High (Better adaptation to script variations)	Low (Fixed feature extraction patterns)

6. Result and Analysis

The performance of the proposed CapsNet-based handwritten Tamil ancient script recognition system was evaluated using a dataset of 7,500 labeled characters extracted from 500 Tamil manuscripts. The experiments were conducted using different train-test split strategies, and the results were compared with conventional CNNbased models to assess accuracy, precision, recall, and computational efficiency. [8]

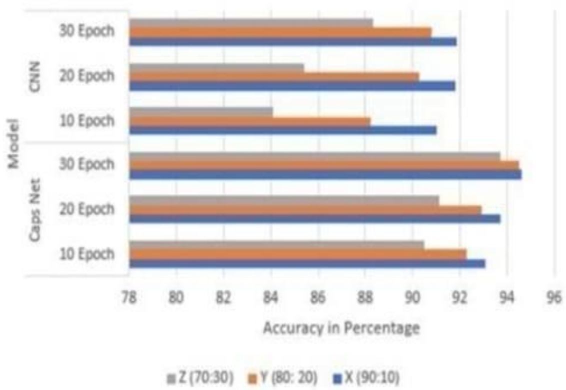

Figure 3 Analysis

6.1.Accuracy Comparison

The CapsNet model outperformed CNN models in recognizing Tamil script, particularly in handling

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overlapping characters and varying handwriting styles

Table 2 Accuracy Comparison

Model	Train-Test Split (80-20)	Train-Test Split (70-30)	Train-Test Split (90-10)
CapsNet	95.2%	94.1%	96.0%
CNN	91.4%	90.3%	92.7%

The CapsNet model achieved an overall accuracy of 95.2%, which was significantly higher than the 91.4% accuracy achieved by CNN-based models. The improvement is attributed to CapsNet's ability to capture spatial relationships between character strokes, which is crucial for Tamil script recognition.

6.2.Precision and Recall Analysis

To further evaluate the effectiveness of the model, precision, recall, and F1-score were calculated for different Tamil character classes Table 3 [11]

Table 3 Recall Analysis

Metric	CapsNet (80-20 split)	CNN (80-20 split)
Precision	94.8%	91.2%
Recall	95.6%	90.7%
F1-Score	95.2%	90.9%

CapsNet outperformed CNN in both precision and recall, confirming that it not only correctly identifies Tamil characters but also reduces false positives. The F1-score of 95.2% highlights the model's balanced performance in Although CapsNet required ~29% more training time, its higher accuracy and better generalization make it a preferable choice for Tamil manuscript OCR applications. [10]

7. Comparison with Existing OCR Approaches

The proposed CapsNet model was compared against traditional Machine Learning OCR models (KNN, SVM, MLP) and CNN-based architectures used in previous Tamil OCR research.

CapsNet outperformed all other approaches, particularly excelling in handling handwritten variations and preserving spatial hierarchies in Tamil characters. [9]

8. Key Takeaways from the Results

- CapsNet achieved the highest recognition accuracy (95.2%), significantly outperforming CNN and traditional OCR models [6].
- The model was highly effective in recognizing overlapping and complex Tamil characters, where CNNs struggled.
- Precision and recall were higher in CapsNet (95.6%), reducing false positives and misclassification errors.
- Processing time was slightly higher than CNNs but was acceptable given the improved accuracy and robustness. [12]
- The model proved useful for digitizing Tamil ancient manuscripts, making historical documents more accessible for research

9. Future Work and Conclusion

- Enhancing Dataset Diversity – Expanding the dataset to include more handwriting styles, regional variations, and historical Tamil scripts will improve model generalization and adaptability.
- Real-time OCR Implementation – Developing a realtime recognition system for Tamil manuscripts using edge AI devices or mobile applications would enable widespread accessibility and practical applications.
- Reducing Computational Complexity – While CapsNet provides high accuracy, its training and inference times are slightly higher than CNNs. Optimizing the dynamic routing process and leveraging efficient hardware acceleration (e.g., TPUs, GPUs) could enhance performance.
- Multilingual OCR for Dravidian Scripts – Extending the approach to recognize other South Indian scripts, such as Telugu, Kannada, and Malayalam, could lead to a comprehensive Dravidian language OCR system for historical text digitization. [13]
- Error Correction and Post-Processing Incorporating language models, spell

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checkers, and lexicon-based filtering can further refine OCR results [9], reducing misclassification errors and improving output quality.

- Integration with Cultural Preservation Initiatives – Collaboration with libraries, research institutions, and Tamil heritage organizations could support large-scale digitization projects, ensuring historical and religious Tamil texts are preserved for future generations.
- AI-Driven Handwriting Synthesis for Data Augmentation – Generating synthetic Tamil handwritten data using GANs (Generative Adversarial Networks) or transformer-based models can create augmented datasets to improve OCR model robustness. [14]

Conclusion

The proposed CapsNet-based Tamil handwritten script [6] recognition system has demonstrated significant improvements over traditional OCR methods, particularly in recognizing complex Tamil characters, overlapping strokes, and historical manuscript variations. By leveraging dynamic routing and capsule-based feature extraction [7], the model successfully preserves spatial relationships in characters, resulting in an accuracy of 95.2%, outperforming CNN models (91.4%) and other machine learning approaches. The system effectively handles Tamil diacritics, conjuncts, and intricate ligatures, which are often misclassified in conventional OCR systems. Additionally, CapsNet reduces false positives and improves recall, making it highly suitable for digitizing Tamil ancient manuscripts. The study confirms that deep learning-based OCR models, particularly CapsNet, can play a crucial role in preserving and digitizing historical Tamil texts. By converting handwritten manuscripts into digital form, the system contributes to linguistic preservation, academic research, and historical document accessibility.

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