**Handwriting Recognition using ML**

**Literature Review**

1. A Bidirectional LSTM approach for written script auto evaluation using keywords-based pattern matching

The literature review of the paper titled "A Bidirectional LSTM approach for written script auto evaluation using" focuses on the development of a system that uses deep learning models, particularly Bidirectional Long Short-Term Memory (BiLSTM) and Convolutional Recurrent Neural Networks (CRNN), for automated evaluation of handwritten scripts. Here is a summary of the key aspects discussed:

1. **Existing Approaches and Challenges**:
   * Traditional methods like Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) are often challenged by the vanishing gradient problem, which limits their effectiveness in tasks like handwriting recognition.
   * Handwriting recognition is a complex task that involves various stages, including acquisition, feature extraction, classification, and recognition. However, storing and processing physical records is inefficient and prone to data loss.
2. **Proposed Solution**:
   * The paper proposes a model using BiLSTM combined with CRNN to address these challenges. BiLSTM allows scanning text from both directions, improving recognition accuracy and solving the vanishing gradient problem encountered by CNNs.
   * The system is designed to auto-evaluate handwritten scripts by converting them into text, matching them with predefined keywords, and generating scores that mimic human evaluation.
3. **Technical Contributions**:
   * The model utilizes handwriting datasets like IAM and Washington to train and validate the system. The output includes the percentage of keyword matches, word error rates, and misspelled words, which help automate the grading process.
   * The literature review compares the proposed model with other handwriting recognition models, highlighting its superiority in terms of accuracy, efficiency, and recognition rates.
4. **Related Work**:
   * The review mentions various studies that have contributed to the field of handwritten text recognition using different neural network models and algorithms. The paper aims to address gaps identified in these studies by integrating BiLSTM with CRNN to improve performance and accuracy.
5. **Benefits**:
   * The proposed system is expected to save time for teachers by automating the evaluation of handwritten scripts, making it a valuable tool in educational settings, especially in the context of online examinations where handwritten responses need to be uploaded and assessed digitally.
6. An online multilingual numeral dataset on Devnagari and English languages for pattern recognition research

**Overview**

The paper introduces a novel dataset of air-written numerals for the Devnagari and English languages, designed for pattern recognition research. The dataset addresses the need for multilingual numeral datasets in real-time numeral recognition applications, which are becoming increasingly relevant in various fields such as online education, healthcare, and banking.

**Related Work**

The development of multilingual numeral datasets for pattern recognition has been an area of active research, particularly in languages like English. However, there is a scarcity of similar datasets for Devnagari, a widely used script in India. Prior research has focused predominantly on handwritten numeral datasets, but the air-written approach presents unique challenges and opportunities, particularly in terms of gesture recognition and the real-time application of these datasets in dynamic environments.

**Dataset Characteristics**

The dataset comprises 20,000 images, with 10,000 images each for Devnagari and English numerals. The data was collected from 100 individuals aged between 20 and 40, using a standard video camera setup. Each participant wrote the digits 0-9 ten times in both scripts. The data collection process was designed to ensure a diverse set of handwriting styles, which is crucial for developing robust pattern recognition algorithms.

**Applications**

The dataset has broad applications across various sectors. In healthcare, for example, it can facilitate air-writing systems in sterile environments like operation theaters. In education, it enables the development of virtual whiteboards, enhancing remote learning experiences. The banking sector can use such systems for secure, contactless interactions, which are particularly beneficial for individuals with physical limitations.

**Challenges and Future Work**

The primary challenges in developing this dataset included ensuring the accuracy of fingertip detection and managing the noise introduced by hand tremors or uncontrolled environments. Future work could explore the integration of more advanced sensors or machine learning models to improve the robustness and applicability of air-written numeral recognition systems.

1. A novel invariant mapping applied to hand-written Arabic character recognition

**1. Introduction**

* **1.1 Purpose**: State the purpose of the Product Management Plan, which outlines the approach to managing the development and delivery of the product.
* **1.2 Scope**: Define the scope of the product and its objectives, including key milestones, stakeholders, and deliverables.
* **1.3 Document Overview**: Brief overview of the document’s structure.

**2. Product Overview**

* **2.1 Product Vision and Goals**: Describe the overall vision of the product and the goals it aims to achieve.
* **2.2 Product Features and Requirements**: Summarize the key features and requirements of the product.
* **2.3 Target Market and Audience**: Identify the target market segments and audience.

**3. Product Development Approach**

* **3.1 Development Methodology**: Explain the methodology chosen for product development (e.g., Agile, Waterfall).
* **3.2 Project Phases**: Outline the project phases, from initiation to completion.
* **3.3 Key Deliverables**: List the critical deliverables for each phase of the product development lifecycle.

**4. Product Roadmap**

* **4.1 Timeline**: Provide a high-level timeline that highlights major milestones.
* **4.2 Key Milestones**: Identify key milestones such as product releases, beta testing, and market launch.
* **4.3 Dependencies and Risks**: Discuss dependencies between tasks and potential risks, including mitigation strategies.

**5. Product Lifecycle Management**

* **5.1 Version Control**: Describe how product versions will be managed and tracked.
* **5.2 Change Management**: Outline the process for managing changes to the product scope or features.
* **5.3 End-of-Life Plan**: Explain the plan for phasing out the product when it is no longer viable.

**6. Product Team and Stakeholders**

* **6.1 Roles and Responsibilities**: Define the roles and responsibilities of the product team and key stakeholders.
* **6.2 Communication Plan**: Detail how communication will be managed among the product team and stakeholders.
* **6.3 Training and Support**: Provide an outline for training sessions and support systems for the product team.

**7. Budget and Resource Management**

* **7.1 Budget Allocation**: Provide a detailed breakdown of the budget allocated to different phases of the project.
* **7.2 Resource Allocation**: Define how resources (human, technical, financial) will be allocated and managed.
* **7.3 Cost Management**: Discuss strategies for monitoring and controlling project costs.

**8. Performance Measurement and Reporting**

* **8.1 Key Performance Indicators (KPIs)**: Define the KPIs that will be used to measure the product's success.
* **8.2 Reporting Structure**: Outline the structure and frequency of performance reports.
* **8.3 Review Process**: Describe the process for regularly reviewing the product’s progress and making necessary adjustments.

**9. Risk Management**

* **9.1 Risk Identification**: List the potential risks associated with the product development.
* **9.2 Risk Assessment and Mitigation**: Provide an assessment of the identified risks and propose mitigation strategies.
* **9.3 Contingency Planning**: Outline contingency plans for managing high-impact risks.

**10. Product Launch Plan**

* **10.1 Launch Strategy**: Discuss the strategy for launching the product into the market.
* **10.2 Marketing and Sales Plan**: Provide an overview of the marketing and sales strategies.
* **10.3 Post-Launch Support**: Outline the plan for post-launch support, including customer service and feedback mechanisms.

**11. Review and Approval**

* **11.1 Review Process**: Describe the process for reviewing the Product Management Plan.
* **11.2 Approval Process**: Outline the steps required for the PMP’s approval by stakeholders.

1. COMPARISON BETWEEN NEURAL NETWORK AND SUPPORT VECTOR MACHINE IN OPTICAL CHARACTER RECOGNITION

The research into Optical Character Recognition (OCR) has been a significant area within artificial intelligence and pattern recognition. Various techniques have been developed over the years to enhance the accuracy and efficiency of OCR systems. Some of the notable contributions include:

1. **Mathematical Symbol Recognition with SVM (Malon et al., 2008)**:
   * Malon and his team focused on recognizing mathematical symbols using Support Vector Machines. Their study showed a significant improvement in classification accuracy, reducing errors by 41% using the SVM method.
2. **Character Recognition Using Back Propagation (Rao et al., 2016)**:
   * Rao and colleagues proposed a modified back-propagation method for OCR. Their method achieved a remarkable accuracy of 100%, demonstrating the potential of neural networks in OCR tasks.
3. **Projection Feature Extraction in Hand-Written Character Recognition (Mahto, Bahtia, and Sharma, 2015)**:
   * This study employed a combination of horizontal and vertical projection features to recognize handwritten Gurmukhi characters. Using linear SVM, the researchers achieved an accuracy of 98.06%, highlighting the effectiveness of projection-based feature extraction.
4. **Zoning Based Feature Extraction (Murthy and Hanmandlu, 2015)**:
   * Murthy and Hanmandlu introduced a zoning-based feature extraction technique, which accounted for black pixel locations to enhance feature uniqueness. This approach achieved over 98.5% accuracy using an SVM classifier.

The existing studies suggest that both SVM and Neural Networks have been successful in OCR applications, with different techniques such as zoning algorithms, projection profiles, and Histogram of Oriented Gradients (HOG) contributing to their effectiveness. However, there appears to be a gap in combining these methods for feature extraction, which this paper aims to address by comparing the performance of SVM and NN using various feature extraction techniques in OCR tasks.

1. Deep learning for ancient scripts recognition

**Overview of Existing Research**

The field of handwritten character recognition, especially for ancient scripts, has evolved significantly over the past few decades. Early research focused on various image processing techniques, such as Gaussian filters, zoning, and structural feature extraction methods. These traditional methods have been applied across various languages, including English, Marathi, Telugu, and Devanagari.

**Challenges in Recognizing Ancient Scripts**

Ancient manuscripts, particularly those written in regional languages like Devanagari, pose unique challenges. The deterioration of text, ink stains, torn pages, and the presence of bilingual text increase the difficulty of recognition. Additionally, Devanagari scripts involve complex elements like modifiers, conjuncts, and shirorekha (header lines), which further complicate recognition tasks.

**Evolution of Deep Learning Models**

Recent advancements in deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have significantly improved the accuracy of character recognition systems. These models have been extended to address specific challenges in recognizing Devanagari scripts. For instance, CNNs have been used for feature extraction, while LSTMs (a type of RNN) have been employed for sequential modeling to handle the temporal dependencies in the scripts.

**Limitations of CNNs**

While CNNs have demonstrated effectiveness in various recognition tasks, they have inherent limitations, including the inability to account for spatial hierarchies between features and rotational invariance. To overcome these challenges, Capsule Networks (CapsNet) have been introduced, which improve spatial awareness and rotation invariance.

**Recent Approaches**

The combination of CapsNet with LSTM represents a recent approach to address the limitations of traditional models. This hybrid model has been shown to capture higher-level features and temporal dependencies effectively, making it suitable for recognizing complex Devanagari characters.

**Conclusion**

The literature indicates a progressive shift from traditional image processing techniques to more sophisticated deep learning models in the domain of ancient script recognition. Despite significant advancements, challenges remain in achieving higher accuracy and efficiency, particularly for complex scripts like Devanagari. The proposed CapsNet-LSTM model represents a promising direction in overcoming these challenges.

1. Device-free multi-modal

Handwriting recognition has traditionally relied on three main schemes: **visual-based**, **wearable sensor-based**, and **wireless signal-based** methods.

1. **Visual-based Scheme**: This approach typically uses images captured from mobile devices and applies deep learning techniques for character classification. For example, a convolutional neural network (CNN) was used in HCCR for high-accuracy recognition of handwritten characters. However, these methods are highly sensitive to lighting conditions, making them less reliable in variable environments.
2. **Wearable Sensor-based Scheme**: Devices like smartwatches or smartpens equipped with inertial sensors record hand movements to recognize characters. For instance, Pentelligence leverages sensors for recognizing handwritten numerals, and other studies have used similar setups for classifying Chinese characters. Despite their effectiveness, these methods require users to wear sensors, which can be uncomfortable and intrusive.
3. **Wireless Signal-based Scheme**: This method does not require direct contact with the user. Techniques like Wi-Fi sensing track gestures and motions through channel state information (CSI). Systems like Wi-Wri and WiReader use this data for handwriting recognition. However, these methods require additional equipment and are prone to signal interference, affecting accuracy.

To address the limitations of these methods, the paper introduces **DMHC (Device-free Multi-modal Handwritten Character Recognition System)**. DMHC combines ultrasonic and general acoustic signals, offering a noise-resistant solution that does not require additional equipment or favorable lighting conditions. The system overcomes challenges such as environmental noise and signal interference by fusing the strengths of both ultrasonic and acoustic signals. This fusion approach ensures robust character recognition even in complex environments.

**Summary of Contributions**

The paper contributes by:

* Designing a multi-modal handwritten character recognition system that fuses ultrasonic and audio signals.
* Proposing an anti-interference method for handwritten signal segmentation.
* Demonstrating the robustness of DMHC through extensive experiments, showing high recognition accuracy under various conditions.

1. Enhanced ResNet-151-based fused features for optimized

The paper primarily discusses the advancements and methodologies in Handwritten Character Recognition (HCR) with a focus on the challenges and solutions associated with recognizing handwritten characters in Indian languages. The literature review section explores various deep learning and machine learning techniques that have been employed to tackle these challenges.

**1. Deep Learning Methods**

* **Li et al. (2020)** developed a matching network to associate handwritten characters with template characters using Chinese characters. Their model outperformed existing CNN-based classifiers in identifying new characters through feature learning, bypassing traditional softmax regression layers.
* **Kavitha and Srimathi (2022)** implemented a CNN-based approach for offline recognition of handwritten Tamil characters. Their method, which was trained from scratch, achieved superior accuracy on both training and testing datasets compared to conventional HCR methods.
* **Sarkhel et al. (2017)** introduced a Multi-column Multi-scale Convolutional Neural Network (MMCNN) for Indic script recognition, demonstrating superior performance across multiple public datasets through a deep quad-tree-based segregation prediction approach.
* **Fu and Xu (1998)** developed a Bayesian Decision-Based Neural Network (BDNN) for multi-linguistic handwritten character recognition. Their Self-growing Probabilistic Decision-based Neural Network (SPDNN) model successfully applied hierarchical network structures to achieve high accuracy in identifying both alphanumeric and Chinese characters.
* **Pareek et al. (2020)** enhanced an offline HCR system for Gujarati script using a dataset comprising 10,000 images. Their CNN and Multi-Layer Perceptron (MLP) based model showed significant improvements in recognition accuracy.
* **Aarif and Poruran (2020)** developed OCR-Nets, a variant of GoogleNet and AlexNet, to recognize Urdu handwritten letters through transfer learning, achieving superior performance compared to traditional character recognition models.

**2. Machine Learning Methods**

* **Sahlol et al. (2020)** proposed a hybrid machine-learning model using rough sets in conjunction with the Binary Whale Optimization Algorithm for selecting optimal features in Arabic handwritten character recognition. Their model outperformed several deep learning models like Inception, Resnet, and VGGnet in terms of accuracy and processing time.

The literature highlights the diversity of approaches and the continual evolution of techniques aimed at improving the accuracy and efficiency of HCR systems, especially for complex scripts such as those in Indian languages. The authors emphasize the need for more sophisticated models, like the one proposed in their work, to overcome the limitations observed in existing methodologies. Their proposed model integrates deep learning with an optimized meta-heuristic algorithm to enhance recognition performance, particularly in real-time applications.

1. Exploration of advancements in handwritten document

**1. Historical Context and Importance of HDR**

The paper begins by emphasizing the importance of HDR in digitizing handwritten documents, which include various elements such as text, diagrams, mathematical expressions, numerals, and tables. The challenges in HDR stem from the variability in writing styles and the complexity of handwritten content, making it a critical area of research in computer vision and artificial intelligence. The ability to accurately recognize and digitize handwritten documents is crucial for preserving historical manuscripts, improving data accessibility, and enhancing human-computer interactions.

**2. Bibliometric Survey**

The bibliometric survey presented in the paper analyzes research trends in HDR based on the number of articles, citations, prolific authors, countries with active research, and network mapping. The survey is based on data extracted from the Scopus database, covering a period of 30 years. The paper notes a significant increase in HDR research post-2018, which coincides with the global push towards digitization, accelerated by the COVID-19 pandemic. The survey highlights that India leads in HDR research publications, followed by China and the United States.

**3. Systematic Review of HDR Techniques**

The systematic review in the paper categorizes HDR techniques into several key areas:

* **Text Recognition:** Techniques for recognizing handwritten text, which have evolved from template matching to more sophisticated methods like neural networks and support vector machines (SVM).
* **Digit Recognition:** The paper reviews methods specifically designed for recognizing handwritten digits, which have been a significant focus due to the availability of large datasets like MNIST.
* **Mathematical Expression Recognition:** Techniques for recognizing handwritten mathematical expressions, which are particularly challenging due to the need to understand complex symbols and their spatial relationships.
* **Diagram and Table Recognition:** The recognition of diagrams and tables within handwritten documents, which requires methods that can interpret both the visual structure and the content.

**4. Challenges and Future Directions**

The paper discusses the challenges in HDR, such as achieving high accuracy across diverse handwriting styles and languages. It emphasizes the need for robust and adaptable algorithms that can handle the complexities of different manuscript forms. The review also identifies gaps in the current research and suggests future directions, including the development of more generalized HDR systems that can be applied across various domains.

**5. Conclusion**

The review concludes by highlighting the significance of HDR in various fields, from preserving cultural heritage to enhancing modern business processes. The paper's comprehensive survey of the literature serves as a valuable resource for researchers and provides a foundation for future advancements in HDR technologies.

1. FUZZY ARTMAP AND MLP NEURAL

**Key ESG Trends and Best Practices:**

1. **Integration and Standardization of ESG Reporting:**
   * The global push for standardized ESG reporting is strong, with frameworks like the Global Reporting Initiative (GRI) and Sustainability Accounting Standards Board (SASB) leading the way. The emphasis is on creating unified, comparable metrics that stakeholders can trust. This trend is accelerating as more companies recognize the importance of transparency in ESG performance.
2. **Climate Change and Decarbonization:**
   * Climate change remains a central focus, with companies increasingly setting ambitious decarbonization targets. Net-zero pledges are becoming more common, and there's a push towards science-based targets to ensure that companies' commitments align with global climate goals. The transition to renewable energy sources is also a significant aspect of this trend.
3. **Social Responsibility and Equity:**
   * Social factors, including diversity, equity, and inclusion (DEI), have gained prominence. Companies are under pressure to improve their social impact by addressing issues such as gender and racial inequality, fair labor practices, and community engagement. The rise of the "S" in ESG reflects a broader understanding that social issues are critical to long-term business success.
4. **Governance and Accountability:**
   * Strong governance structures are crucial for effective ESG implementation. Best practices in governance include clear accountability mechanisms, robust board oversight, and stakeholder engagement. There is also a growing focus on executive compensation linked to ESG performance, ensuring that leadership is aligned with sustainability goals.
5. **Investor and Regulatory Pressure:**
   * Investors are increasingly factoring ESG considerations into their decision-making processes. Regulatory bodies worldwide are also stepping up, with new regulations mandating ESG disclosures and penalizing non-compliance. This dual pressure is pushing companies to prioritize ESG issues more than ever.
6. **Technological Innovation and Data-Driven ESG:**
   * The use of technology, particularly data analytics, AI, and blockchain, is transforming ESG practices. These technologies enable more accurate tracking of ESG metrics, better risk management, and enhanced transparency. Companies that leverage these tools effectively can gain a competitive edge in their ESG performance.
7. **Supply Chain Sustainability:**
   * Supply chain sustainability is a growing concern, with companies being held accountable for the ESG practices of their suppliers. Best practices include rigorous supply chain audits, collaboration with suppliers to improve ESG standards, and the adoption of circular economy principles.
8. **Stakeholder Engagement and Communication:**
   * Engaging with stakeholders, including investors, employees, customers, and the community, is essential for successful ESG strategies. Transparent and consistent communication about ESG efforts helps build trust and can lead to better business outcomes. Companies are increasingly adopting multi-stakeholder approaches to address complex ESG challenges.
9. Grocery shelf images using computer vision and machine learning

The literature on product recognition from grocery shelf images primarily focuses on developing automatic systems that leverage computer vision and machine learning techniques to enhance various aspects of retail management. These systems aim to automate the recognition and tracking of products on grocery shelves, offering benefits such as efficient inventory management, improved customer experience, accurate pricing, and personalized marketing.

**1. Product Recognition Methods**

* **Barcode and RFID Technologies**: Traditionally, barcode scanning and RFID have been used for product recognition. Barcodes require line-of-sight scanning, which can slow down the process and is vulnerable to physical damage. RFID, while effective, has limitations related to security concerns and limited range.
* **Computer Vision and Machine Learning**: With advancements in machine learning and computer vision, more accurate and reliable methods for product recognition have been developed. These technologies analyze product features such as shape, size, and color, reducing errors and improving efficiency compared to traditional methods.

**2. Datasets for Product Recognition**

* The review includes various datasets that have been developed for training and testing product recognition algorithms:
  + **WebMarket Dataset**: One of the first datasets, comprising 3,153 shelf images and 300 template images, primarily used for product recognition on grocery shelves.
  + **Grozi-120 Dataset**: Contains in vitro (template) and in situ (shelf) images, focusing on object recognition and localization.
  + **Grocery Products Dataset**: A fine-grained dataset with hierarchical categorical information, used to test product recognition under various conditions.
  + **Grocery Dataset**: Specifically focused on cigarette packages, providing diverse product images and shelf images from various groceries.
  + **Freiburg Groceries Dataset**: Comprises training images and test images captured with different cameras and under varying conditions, focusing on product recognition in cluttered scenes.
  + **CAPG-GP Dataset**: A fine-grained grocery product dataset, particularly focusing on tube-packed, bag-packaged, and box-like packaged products.

**3. Challenges and Trends**

* **Challenges**: The document discusses the challenges of product recognition, such as dataset complexity, the difficulty of obtaining and updating datasets, and the diversity of product scales and packaging.
* **Emerging Trends**: There is a trend towards adopting machine learning and computer vision-based systems in retail, driven by their ability to integrate with inventory management, supply chain, and logistics systems, and their increasing accessibility due to reduced hardware and software costs.

1. Handwritten Character Recognition

Handwritten character recognition (HCR) has been a significant area of research, particularly with advancements in machine learning and deep learning technologies. The traditional approach to Optical Character Recognition (OCR) systems involves the extraction of features from images of text followed by classification into respective characters. The literature demonstrates a variety of methods that have evolved over time to enhance the accuracy and efficiency of HCR systems.

**Early Approaches and Traditional Methods**

Historically, HCR systems utilized methods such as template matching, where the input character image is compared against a set of stored templates representing different characters. While simple, these methods were limited by their inability to generalize across variations in handwriting styles. Later, feature-based approaches were introduced, where key features like edges, corners, and intersections were extracted from character images and fed into classifiers such as Support Vector Machines (SVM) or k-Nearest Neighbors (k-NN). Although more robust than template matching, these methods were still prone to errors, especially with complex and noisy inputs.

**The Emergence of Deep Learning**

The introduction of Convolutional Neural Networks (CNNs) marked a significant leap in the field of HCR. CNNs, due to their ability to automatically learn hierarchical features from raw pixel data, significantly outperformed traditional feature-based methods. The architecture of CNNs, comprising layers of convolutional filters followed by pooling and fully connected layers, is particularly well-suited for image classification tasks, including character recognition. Notable early CNN architectures like LeNet and AlexNet laid the groundwork for modern OCR systems.

**Hybrid Models: CNN-ECOC**

The paper focuses on a hybrid model combining CNNs with Error Correcting Output Codes (ECOC) for HCR. ECOC is a technique that improves the robustness of multi-class classifiers by converting a multi-class problem into multiple binary classification problems. The CNN-ECOC model leverages the feature extraction capabilities of CNNs with the classification robustness of ECOC, thereby addressing some of the limitations of traditional softmax classifiers used in CNNs.

The hybrid approach has been tested on the NIST handwritten character dataset, showing improved accuracy compared to standalone CNN models. The combination of CNN for feature extraction and ECOC for classification is particularly beneficial in scenarios where the handwriting is varied or complex, as ECOC helps in reducing the classification errors by incorporating a coding scheme that maximizes the hamming distance between class codewords.

**Comparison with Other Architectures**

The paper also discusses various CNN architectures like AlexNet, ZfNet, and LeNet, each contributing differently to the field of OCR. AlexNet, with its deep architecture and use of ReLU activation and dropout for regularization, provided significant improvements in object recognition tasks. ZfNet refined some of the architectural choices of AlexNet, such as filter sizes and strides, to achieve better performance. LeNet, on the other hand, was one of the pioneering CNN architectures specifically designed for digit recognition, and it laid the foundation for subsequent developments in the field.

In recent years, other researchers have also explored the use of CNNs for recognizing handwritten characters in different languages, achieving notable accuracy levels. For instance, Rahman et al. developed a CNN-based model for Bangla script recognition, which achieved an accuracy of over 85%, highlighting the adaptability of CNNs across different scripts and languages.

1. Japanese historical character recognition

The research on Japanese historical character recognition, specifically kuzushiji, has gained significant traction due to the increasing need for digitalizing historical documents. Kuzushiji are cursive Japanese characters that appear in many historical texts, and their recognition is essential for preserving and accessing Japan's cultural heritage. The primary challenge in kuzushiji recognition is the imbalance in sample distribution, where a significant number of characters have very few or no samples at all, which drastically affects recognition performance.

Several methods have been developed to address kuzushiji recognition. The release of the Kuzushiji Dataset in 2016 marked a critical point, leading to more active research in this field. Clanuwat et al. introduced Kuzushiji-MNIST (KMNIST) and Kuzushiji-49 datasets, which were designed to be more accessible for researchers by offering a more tractable version of the dataset. These datasets are compatible with the well-known MNIST but are significantly more challenging due to the complexity of kuzushiji characters.

Various approaches have been employed to enhance the recognition of kuzushiji. For instance, CNN architectures with advanced techniques like DropBlock have been used for improved recognition accuracy. Methods like YOLO and ResNet have also been adapted for kuzushiji detection and recognition, showing significant promise in tackling this challenge. Notably, KuroNet, which employs U-Net architecture, was developed to perform detection and recognition directly from historical book images, representing a significant advancement in the field.

The literature highlights that while these methods achieve high accuracy with a large number of samples, their performance declines sharply with few-sampled characters. This has led to the development of novel techniques focusing on character parts, enabling recognition even with minimal samples. The proposed methods leverage the structure of characters, such as using the spatial organization of radicals in Chinese characters, to improve zero-shot recognition—where the model is tested on characters it has never seen during training.

Recent advancements also involve pre-training models on synthesized images of non-existent characters to overcome the imbalance in sample sizes. This approach helps in learning robust features that are transferable to real kuzushiji characters, thereby enhancing the recognition of rare and unseen characters.

1. Odia character recognition system

 **Optical Character Recognition (OCR) Overview**:

* OCR has been a significant area of research for over 50 years, aiming to convert printed or handwritten text into editable digital formats.
* The study distinguishes between printed character recognition and handwritten character recognition (HCR), emphasizing the complexity of HCR due to the variability in individual handwriting styles.

 **Feature Extraction Techniques**:

* Feature extraction is crucial for reducing the dimensionality of input data while preserving the characteristics necessary for accurate classification.
* The paper discusses various approaches to feature extraction, including both feature selection (choosing a subset of features) and feature extraction (transforming input data into a smaller dimensional space).

 **Review of Previous Research**:

* The paper reviews numerous studies conducted between 2005 and 2020, focusing on different feature extraction methods and classification techniques used for Odia character recognition.
* Early research includes works by Roy et al. (2005), who used a chain code histogram-based method, and Bhowmik et al. (date not mentioned), who applied Hidden Markov Models (HMMs) with a recognition accuracy of 90.50%.
* Subsequent studies introduced methods like Quadratic Classifiers, Principal Component Analysis (PCA), neural networks, and Genetic Algorithms, all aimed at improving recognition accuracy.

 **Challenges and Limitations**:

* The paper notes that despite progress, challenges remain in achieving high accuracy due to the distinct nature of Odia script, which features curvatures and variations in writing styles.
* It is highlighted that research on Odia OCR was relatively sparse until 2012, and even afterward, significant improvements were needed.

 **Advantages and Disadvantages of Techniques**:

* The review includes a table summarizing the strengths and weaknesses of different OCR methods, noting that no single method is universally applicable, and the choice of technique often depends on the specific dataset and problem context.

 **Future Directions**:

* The authors suggest that future research should focus on creating more comprehensive datasets and exploring new feature extraction methods to improve the recognition of handwritten Odia characters.

1. Oracle character recognition using unsupervised discriminative consistency

The paper titled "Oracle Character Recognition Using Unsupervised Discriminative Consistency Network" focuses on addressing the challenges in oracle character recognition (OrCR), specifically dealing with the unique characteristics of oracle bones, such as abrasion, stain, and distortion. These issues make it difficult to collect and annotate real-world scanned oracle characters, which poses a significant challenge for recognition tasks. The authors propose an unsupervised domain adaptation (UDA) method that leverages pseudo-labeling and consistency regularization to improve model robustness and feature discrimination.

**Related Work:**

1. **Oracle Character Recognition (OrCR):**
   * **Early Methods:** Early studies on OrCR involved hand-crafted features based on graph theory and topology to recognize oracle characters. These methods primarily focused on topological relations and features like curvature histograms.
   * **CNN-Based Approaches:** With the advent of deep learning, CNNs have been increasingly utilized for OrCR. Several models such as AlexNet, VGGNet, ResNet, and OracleNet have been applied, achieving significant improvements in classification tasks. These models often use triplet loss, Capsule networks, or generative adversarial frameworks to enhance recognition performance.
   * **Limitations:** Despite the success of CNNs, the need for massive labeled data remains a significant barrier. The lack of annotated oracle characters makes supervised learning less feasible, necessitating the exploration of UDA techniques.
2. **Unsupervised Domain Adaptation (UDA):**
   * **Common UDA Techniques:** UDA methods like discrepancy reduction and adversarial learning have been widely studied. Techniques such as Maximum Mean Discrepancy (MMD), Central Moment Discrepancy (CMD), and domain adversarial neural networks (DANN) have been employed to align the distributions of source and target domains.
   * **Pseudo-Labeling:** Pseudo-labeling, often used in conjunction with consistency regularization, has gained popularity in UDA for improving model robustness. Methods like Fixmatch and AsmTri employ pseudo-labeling to generate labels for unlabeled data and enhance the consistency of model predictions across different augmentations.
   * **Challenges in OrCR:** Applying UDA to OrCR is particularly challenging due to the unique nature of oracle characters, such as severe abrasion and high intra-class variance. Existing UDA methods often struggle with these challenges, leading to limited performance improvements.

**Summary of Contributions:**

The authors propose a novel UDA method, the Unsupervised Discriminative Consistency Network (UDCN), which focuses on enhancing model robustness and learning discriminative features for scanned oracle characters. The method introduces augmentation consistency and an unsupervised transition loss to improve performance significantly. The UDCN achieves state-of-the-art results on the Oracle-241 dataset, outperforming previous methods like the structure-texture separation network by a substantial margin. This work highlights the potential of combining UDA with advanced consistency techniques to improve the accuracy of OrCR, thereby bridging the gap between artificial intelligence and historical studies.

1. Recognition using Tesseract with the Javanese Script Target

**Key Points from the Literature Review:**

1. **Optical Character Recognition (OCR) in Computer Vision**:
   * OCR is a critical application in the field of computer vision, used to convert scanned images or printed documents into editable text formats. It has various applications such as license plate recognition, text recognition in traffic signs, and document digitization.
2. **Challenges in Non-Latin Script OCR**:
   * Most OCR research has focused on Latin scripts, leaving non-Latin scripts, such as Javanese, relatively unexplored. Non-Latin scripts present unique challenges due to their distinct contours and shapes, which differ significantly from Latin scripts.
3. **Previous Work on OCR**:
   * Various methods have been developed to improve OCR accuracy. For example, Phangtriastu et al. (2017) combined features like zoning algorithms and projection profiles with classifiers like Support Vector Machines (SVMs) to achieve high accuracy in character recognition.
   * Mithe, Indalkar, and Divekar (2013) presented a method using the Tesseract OCR engine for Android, focusing on segmentation, feature extraction, and classification.
4. **Specific Research on Non-Latin Scripts**:
   * Chanda et al. (2018) addressed the problem of recognizing Han-based scripts (e.g., Chinese, Japanese, Korean) using directional chain-code histograms and Support Vector Machines, achieving high accuracy.
   * Dewa, Fadhilah, and Afiahayati (2019) implemented Convolutional Neural Networks (CNN) for Javanese script recognition, though with lower accuracy compared to Latin script OCR.
5. **Gap in Research**:
   * Despite advancements in OCR, there is still a significant gap in research focused on non-Latin scripts, particularly Javanese, which lacks publicly available datasets and comprehensive studies.

The document underscores the importance of developing specialized OCR systems for non-Latin scripts like Javanese and presents the current study as a step toward filling this gap by creating datasets and testing different OCR methodologies using Tesseract.

1. Smart flower gradient descent

The literature review of the paper titled "Smart Flower Gradient Descent Optimization Enabled Generative Adversarial Network for Recognition of Tamil Handwritten Character" highlights various approaches and challenges in Tamil handwritten character recognition.

1. **Introduction to Handwritten Character Recognition (HCR):** The paper discusses the complexity of recognizing Tamil handwritten characters due to the language's unique structure, including its vowels, consonants, compound alphabets, and the variations in handwriting styles among individuals. Tamil handwritten character recognition is described as more challenging compared to other languages due to the inclusion of numerous modifiers, angles, and large character sets.
2. **Existing Methods:**
   * Several existing models are reviewed that focus on the recognition of handwritten Tamil characters. For instance, Lincy RB et al. developed a model using the Self Adaptive Lion Algorithm (SALA) combined with a Convolutional Neural Network (CNN) for recognizing characters. Despite its scalability, it was time-consuming.
   * Kowsalya S. et al. used a modified Artificial Neural Network (ANN) combined with Elephant Herding Optimization to achieve a high recognition rate, but they failed to incorporate other classifiers that could have improved efficiency.
   * Devi S. G. et al. applied CNN for recognizing cursive Tamil characters in palm leaf manuscripts. Although the approach was effective in identifying structural patterns, it couldn't eliminate undesirable cursive writing.
   * Raj M. et al. developed a model using a PM-Quad tree and Z-ordering algorithm to recognize Tamil letters, though it did not consider the statistical features of handwritten characters.
   * Other approaches, including those by Gnanasivam P. and Shanmugam K., utilized deep learning and convolutional networks for Tamil character recognition. These methods showed promising results but suffered from issues like ambiguity due to similar characters and inconsistencies in handwriting.
3. **Challenges:**
   * Many of the previous methods lacked robust pre-processing models that could preserve the original shape of characters despite variations in pen width, background, and ink type.
   * Issues such as inadequate optimization of input parameters, structural complexity, and difficulties in dealing with free-form handwritten characters limited the performance of the models.
4. **Proposed Solution:** The paper introduces a novel Smart Flower Gradient Descent Optimization (SFGDO)-enabled Generative Adversarial Network (GAN) for Tamil handwritten character recognition. The SFGDO combines Smart Flower Optimization Algorithm (SFOA) and Gradient Descent Optimization (GDO) to enhance the recognition accuracy and convergence rate of the model. This method addresses several limitations of previous approaches by improving pre-processing, feature extraction, and classification techniques.
5. Tamil Handwritten Character Recognition

Here are key points covered:

1. **Optical Character Recognition (OCR) Techniques**: OCR techniques are split into offline and online methods. Offline OCR is used for scanned documents, while online OCR recognizes characters from real-time input (such as stylus movements). The review emphasizes offline methods due to the complexity of handwritten Tamil characters.
2. **Challenges in Tamil Character Recognition**: Tamil is a complex language with 247 characters, including vowels, consonants, and vowelized consonants. The major challenges include shape variations, writer inconsistencies, structural overlaps, and loops. These complexities make Tamil handwritten character recognition particularly difficult compared to printed character recognition.
3. **Feature Extraction Methods**: Existing research explores various feature extraction methods. Directional features, locational features, and zone-based division are highlighted as critical to improving recognition accuracy. Past approaches used quad tree representations to manage unnecessary loops and curves, a key problem in Tamil handwriting.
4. **Classification Algorithms**: Support Vector Machines (SVM) are commonly applied in the field of handwritten character recognition, especially due to their ability to handle large feature sets. Previous research has experimented with various classifiers but highlights the need for improved accuracy in complex characters.
5. **Datasets**: There has been a lack of comprehensive Tamil handwriting datasets. Previous work primarily used isolated character datasets like those from HP Labs India. However, real-world handwritten datasets from Tamil Nadu, India, have also been used to experiment with these recognition techniques.
6. Temporal-channel cascaded transformer for imagined handwriting character

**Advances in Brain-Computer Interface (BCI)**

Brain-computer interface (BCI) technologies have evolved significantly in recent decades, offering new opportunities for decoding brain activity. Early BCI technologies, such as electroencephalography (EEG) and magnetoencephalography (MEG), are non-invasive methods that monitor brain signals through scalp electrodes. Partially invasive techniques, such as electrocorticography (ECoG), involve placing electrodes directly on the brain's surface. However, invasive technologies such as micro-electrode arrays (MEA) provide more detailed recordings of individual neuron activities by directly interacting with neurons in proximity to the electrodes. MEAs have shown promise in offering a higher temporal and spatial resolution, making them ideal for studying brain cognitive activities like language processing and motor control​.

**Neural Decoding for Imagined Handwriting**

The ability to decode imagined handwriting using brain signals is an emerging area of study in cognitive neuroscience. Previous works focused on decoding brain signals for imagined speech, movements, or phonemes using various methodologies. For instance, ECoG-based methods have been applied to decode isolated phonemes and continuous speech but have limitations in decoding rapid and complex tasks due to their inability to isolate individual neuronal activities. In contrast, MEA signals, with their higher resolution, have shown superior performance in complex tasks like handwriting and motor control decoding​.

**Traditional and Deep Learning Methods in Signal Processing**

For the classification of neural signals, two major approaches are commonly used: traditional signal processing and deep learning. Traditional methods involve pre-processing the raw time-series data using techniques such as wavelet transforms, independent component analysis (ICA), and clustering algorithms. These methods have been effective for tasks with a smaller number of categories, although they struggle with more complex signal sorting and the non-stationary behavior of background activities.

Recent years have seen an increase in the use of deep learning approaches, which offer superior performance by automatically learning feature representations from data. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers have all been applied in decoding tasks. CNNs and RNNs have demonstrated success in decoding brain signals; however, they have limitations in perceiving global dependencies in temporal and channel dimensions​.

**Transformer Models for Neural Decoding**

Transformer models have gained significant attention due to their ability to capture long-term dependencies in sequence data through self-attention mechanisms. Early transformer models have been applied to EEG-based speech recognition and motor imagination classification tasks, showing improvements over traditional methods. Despite these advancements, there has been limited application of transformers in MEA-based signal decoding​.

1. TSP\_CMES\_24555

The literature review in this document covers various aspects of Arabic OCR, which includes the following:

1. **Printed vs. Handwritten OCR**:
   * **Printed OCR** focuses on recognizing text from printed documents, which is generally more straightforward due to uniformity in font and size.
   * **Handwritten OCR** is more challenging due to the variability in handwriting styles, orientations, and resolutions. This type is often used in applications such as postal mail sorting and bank check processing.
2. **Online vs. Offline OCR**:
   * **Online OCR** recognizes text in real-time as it is being written, capturing additional data such as stroke direction and speed, which can enhance recognition accuracy.
   * **Offline OCR** deals with images or documents after they have been created, and is used for both handwritten and printed text. It is more common but generally less accurate than online OCR.
3. **Image and Video-Based OCR**:
   * **Image-Based OCR** processes single images to extract text.
   * **Video-Based OCR** uses multiple frames from a video to improve accuracy, as the repetition of text across frames can help in correct recognition.
4. **Challenges in Arabic OCR**:
   * Arabic OCR faces unique challenges due to the cursive nature of the script, the presence of diacritics, and the rich morphological structure of the language. These factors make it more difficult to segment and recognize text compared to Latin-based languages.
5. **Deep Learning in OCR**:
   * The review highlights the shift from traditional handcrafted feature extraction methods to deep learning techniques such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). These methods have shown superior performance in recognizing complex scripts like Arabic.
6. **Datasets and Evaluation Metrics**:
   * The document discusses the various datasets used for training and evaluating Arabic OCR systems, as well as the metrics used to measure their performance. It points out that many existing systems perform poorly, particularly on page-level scripts, and that improvements are needed.
7. **Comparison of Existing Systems**:
   * The review includes a comparison of commercial and open-source Arabic OCR systems, noting that most current approaches still have relatively low recognition accuracy, especially for complex or page-level text.

The literature review emphasizes the complexity of Arabic OCR and the ongoing need for advancements in this area, particularly with the use of deep learning techniques to overcome the challenges posed by the language's unique characteristics.