

MULTILINGUAL TEXT IDENTIFICATION AND RECOGNITION FROM IMAGE**Pranav Rajendra Patil**Research Scholar
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(Dr. Annasaheb G.D. Bendale Mahila Mahavidhyalaya, Jalgaon, Maharashtra, India)**ABSTRACT:**

Modern digital environments face challenges in extracting and recognizing text from visual media containing multiple languages, especially those with limited linguistic resources. This research aims to address this issue through a threefold objective: (1) detect multilingual text from images, (2) accurately recognize English, Hindi, and Marathi text, and (3) develop an efficient system using integrated visual and language processing techniques. The system is implemented using EasyOCR, OpenCV (cv2), and LangID libraries in a Python environment on Google Colaboratory. Preprocessing steps include grayscale conversion and binarization, followed by text localization and language identification. Social media images were selected as the primary data source due to their diverse multilingual content and contextual richness. The system achieved effective multilingual text recognition, accurately detecting and classifying words among the three targeted languages. Visual inspection confirmed the success of preprocessing, precise bounding box placements, and reliable language categorization. Recognized words such as "Leather," "कम से कम," and "चमडा" demonstrate the system's high accuracy and capability in segmenting and classifying multilingual text. In conclusion, the developed system presents a robust solution for multilingual text extraction from images, with potential applications in digital document conversion, real-time language adaptation, and integration with broader Natural Language Processing (NLP) systems.

Keywords: Multilingual text recognition, Optical Character Recognition (OCR), Image-based text extraction, Natural Language Processing (NLP).

1. Introduction

The present digital age features huge text contents which exist within visuals that spread across multiple platforms which include official document scans and educational materials alongside social media assets and public signs with multiple languages [1]. Due to digital advancement, the field of automatic information retrieval from almost any text containing source has become a trend followed by the research fraternity. This information extraction as well as processing has gradually moved from evaluating texts in digital documents for detecting and analyzing texts present in natural images. The phenomenon stands out most strongly in India and other similar multilingual countries where English coexists with Hindi and Marathi languages in each visual display. Modern interpreting goals for digitization and information access demand precise interpretation of such data due to its crucial function in translation work and accessibility services

and retrieval tasks. The diffusion of almost all earlier publication forms into digital formats on computer networks is significantly impacted by the significant shift from print-based to electronic-based formats brought about by enhanced computing technology. Optical character recognition (OCR) is a vital process that involves the extraction of handwritten or printed text from scanned or printed images, converting it into a format that can be understood and processed by machines. This enables further data processing activities such as searching and editing. Then, reading papers electronically is one of the key responsibilities in machine learning. A high-performance optical character recognizer (OCR) may be used to convert all different areas of documents, publications, reports, and technical papers to electronic form. NOT all present-day Optical Character Recognition (OCR) systems function properly with single-language inputs because they cannot simultaneously detect multiple scripting languages properly [2]. The current limitation reduces both detection precision and text recovery outcomes with special impact on low-resource language data and images of poor quality. These obstacles serve as significant hindrances for the implementation of inclusive digital transformation as well as error-free cross-language content processing [3-4]. The solution of this issue remains crucial due to rising interest in system intelligence that detects images bearing text while performing language classification and segment recognition. The implementation of such an automated system would facilitate better results in document automation together with multilingual accessibility and cross-linguistic content dissemination and the protection of linguistic diversity [5-6].

The research aims to close existing technological limitations in multilingual text processing by examining efficient solutions for detecting and recognizing text contents within image files which contain multiple languages. The study targets research questions about accurate multilingual image text discovery together with segmentation and recognition utilizing modern vision systems and language processing technologies in English, Hindi and Marathi language applications. The proposed research seeks to develop a strong OCR-based system which recognizes various scripts present in a single image. The research goals involve creating a detection model which identifies text areas in multi-language images while recognizing various scripts and subsequently extracts content through machine learning and image processing operations. The system operates under real-time conditions while remaining able to work on mobile platforms and systems with limited resources thus providing extensive deployment possibilities and scalability. The research develops an advanced multilingual image processing system through deep learning architectures which combine traditional OCR techniques and language identification systems. The system's main purpose is to streamline document digitization with precise translation services along with accessibility features that support various multilingual user populations.

2. Review of literature

Research scholars in India have made meaningful contributions to multilingual text recognition during the past years by developing specialties in Hindi and other regional languages similar to Marathi and Tamil. **Jain et al. (2019)** investigated multilingual document analysis while discussing the obstacles which make Indian script recognition difficult due to their varied shapes and hard-to-identify character styles. Their investigation enabled the development of OCR solutions for specific Indian scripts in the country [7]. The authors of **Singh et al. (2020)** conducted an extensive research of multilingual text recognition systems while stressing how deep learning frameworks resolve real-world multilingual data from noisy low-resolution images

[8].

Chakraborty et al. (2020) developed a self-directed learning system specifically designed to function with limited data resources from Hindi and Marathi languages. The approach relied on unlabeled data for accuracy improvement thus helping regions with minimal annotated datasets [9]. The research by **Kar et al. (2020)** showed how models obtain enhanced OCR performance when trained to handle multiple scripts simultaneously within multilingual environmental systems such as English-Marathi and English-Hindi [10]. The authors **Patel and Joshi (2021)** developed a documentation processing platform which integrated CNN-based text location functions with automatic scripting detection techniques for handling Indian documents. The study found English scripts achieved high detection accuracy however detection of Marathi and Gujarati scripts needed additional preprocessing because of their unique stylistic features [11]. **Deshmukh and Borse (2022)** established a lightweight multilingual pipeline through their combination of EasyOCR and OpenCV to be used in real-time mobile scanning which they validated on bilingual official documents. The research indicated OCR systems advance toward NLP techniques as well as deep learning approaches to handle multilingual scene text detection problems. Most current systems face difficulties when trying to separate overlapping text and classify text containing both Devanagari and Roman scripts [12].

Table 1. Summary of Literature Survey

Authors	Year	Languages	Method used	Research Gap	Outcomes
Sharma et al.	2019	Hindi, English	Tesseract OCR + Image preprocessing	Inconsistent accuracy with complex backgrounds and font variations	Moderate recognition accuracy for clean images, limited success on noisy data
Jain et al.	2019	Hindi, English	Survey, rule-based OCR	Difficulty handling mixed scripts and handwritten content	Identified major challenges in Indian OCR
Singh et al.	2020	Hindi, Marathi	Deep learning survey	Lack of hybrid deep learning models for Indian languages	Advocate for hybrid CNN-RNN approaches
Chakraborty et al.	2020	Hindi, Marathi dialects	Self-supervised learning	Handling low-resource scripts efficiently	Improved results in low-resource scripts

Kar et al.	2020	English+ regional mix	Co-occurrence modelling	Lack of context-aware multilingual text segmentation	Boosted performance in multilingual data
Patel and Joshi	2021	Hindi, Gujarati, English	CNN+LangID integration	Need for better preprocessing in multilingual pipelines	High accuracy with preprocessing
Das et al.	2021	Bengali, Devanagari, English	Character segmentation + template matching	Lack of adaptive learning for low-resource scripts	Increased accuracy for printed text, poor results on handwritten samples
Deshmukh and Borse	2022	Hindi, Marathi	EasyOCR+ Mobile pipeline	Lack of lightweight OCR models for mobile and real-time use	Effective for real-time scanning
Bansal et al.	2022	Hindi, Tamil, English	Hybrid CNN-RNN	Difficulty in capturing character-level dependencies across languages	Better sequence recognition and context-aware decoding
Halder et al.	2023	Indic Scripts	Vision Transformer + CTC decoder	Difficulty in scene text recognition for multiple Indic scripts	Improved end-to-end recognition using transformer-based architectures
Roy et al.	2023	Bengali, English	Zone segmentation + SVM classifier	Lack of efficient multilingual	Improved region-wise classification

				segmentation techniques	but limited scalability
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3. Methodology

The research provides a stable process to extract text along with identify languages from social media images through Optical Character Recognition techniques. The procedural aspects include dataset preparation alongside selection of tools and design of algorithms with a detailed processing sequence.

3.1 Dataset description and preparation

The research data consists of more than 500 images that include text material from English and Hindi as well as Marathi languages. Most of these images were acquired from social media platforms that naturally show mixed-language usage in their digital posts and banners and advertisements. The chosen sources provided valuable training data because of their mixed linguistic characteristics which best suit testing a multilingual text recognition system. Images were chosen for the data collection process when they included multiple languages from among the target group. The evaluation of social media content and news banners along with commercial advertisements involved manual selection based on their language content and visual legibility. A human expert applied manual bounds for text identification and associated text sections to support both training and performance checking of the supervised learning model. The data required preprocessing techniques before it could be used for recognition purposes. Standardization procedures included resizing images while converting them to JPEG/PNG formats then applying grayscale processing followed by image binarization to improve visible text features. The implemented noise reduction together with contrast enhancement techniques maximized image clarity among poorly acquired or visually busy samples. The team in Google Colaboratory implemented dataset processing using Python which integrated OpenCV (cv2) for image processing and EasyOCR for multilingual text recognition as well as LangID for automatic language identification. The extensive preparation process makes the dataset resilient to provide precise multilingual text recognition when processing actual images.

3.2 Techniques and Tools

Several programming tools and libraries were selected to achieve both text extraction and language detection functions.

- **Python (Google Colaboratory)** – Primary platform for coding and experimentation.
- **EasyOCR**- This library provides an easy-to-use interface for OCR.
- **OpenCV (cv2)**- OpenCV library is used for computer vision tasks, image processing, and manipulation [13].
- **Langid**- A lightweight language identification library employed to detect the language of extracted text [14].

3.3 Proposed Methodology

The implemented system specializes in identifying and recognizing multiple languages from images while specifically focusing on English along with Hindi and Marathi writing formats. The framework deploys Python on Google Colaboratory to process images through OCR and includes preprocessing of images and detection of text alongside language identification to create visualizations.

3.3.1 Dataset Acquisition

The initial dataset contains social media images which display various languages. The images depict numerous actual scenarios which contain multiscrypt text found across street signs and documents and labels. The diverse range of data in the dataset lets the system undergo a thorough testing of its ability to handle multiple languages.

3.3.2 Tools and Libraries

The following open-source libraries are used for implementation:

- **EasyOCR:** A deep learning-based OCR tool supporting multiple Indian languages including English, Hindi, and Marathi.
- **OpenCV (cv2):** Used for image processing tasks such as grayscale conversion, thresholding, and drawing bounding boxes.
- **Langid:** A lightweight language identification library based on Naive Bayes classification.

3.3.3 Image Preprocessing

Preprocessing operations improve recognition accuracy by being applied to the input images. Converting the image to grayscale turns a multichannel data set into a single channel which helps reduce computational complexity. Adaptive thresholding then follows to perform an image binarization as it helps both highlight text regions and suppress background distractions. Text segmentation becomes more stable through this essential step which enhances the clearness of text portions in input information.

3.3.4 Text Detection and Recognition

The text recognition process uses EasyOCR's `readtext ()` function for the operation. The technique detects textual regions while it extracts textual content along with confidence scores that come with bounding box coordinates. The image receives text placement from OpenCV after processing is complete.

3.3.5 Language Identification

The detected text segments enter the `langid. classify ()` function to receive language identification. The algorithm provides two results consisting of a language identifier such as 'en', 'hi', 'mr' followed by its confidence rating.

3.3.6 System Architecture

The system implements multiple stages that function as a sequential processing pipeline to operate. Text detection serves as the first phase through which connected component analysis teams up with sliding window classification to find text areas in images successfully. The next processing step is text verification that applies geometric analysis with text characteristics to eliminate false positive detections from the region detection results. Text segmentation moves forward when identified text areas undergo a process of binarization along with cropping before recognition can begin. Deep learning-based OCR models process individual regions to create text strings suitable for machine processing after the text segmentation step. Langid evaluates the recognized text segments to assign each section to its native language between English Hindi and Marathi.

3.3.7 Algorithm Steps

- Import the required libraries (`easyocr`, `cv2`, `langid`, `numpy`).
- Initialize the OCR model with multilingual support.

- Read and display the input image.
- Preprocess the image with grayscale and thresholding.
- Apply OCR to extract text and bounding boxes.
- Draw bounding boxes around detected regions.
- Identify the language of each text segment.
- Display recognized text and corresponding language labels.

3.3.8 Visualization and Output

The application identifies recognized text through bounding boxes that appear directly on the input image. Users receive textual content along with language identification for every segment during text recognition while maintenance staff can verify both items for further use.

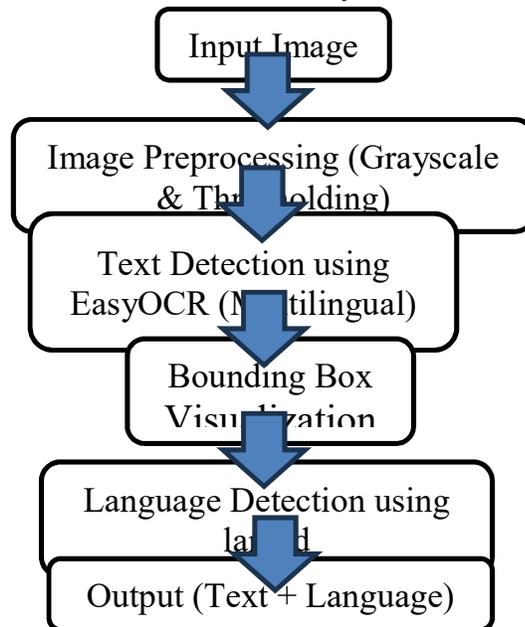


Figure 1: Proposed System

3.4 Experimental process

The developed experimental framework performs multilingual text extraction from images with a systematic processing pipeline which includes text identification together with English Hindi and Marathi language recognition [15]. Implementation of this work follows Python code development in Google Colaboratory that utilizes several open-source Optical Character Recognition (OCR) and language classification libraries. Image preprocessing is applied first to enhance the text visibility while reducing background noise in the scene. The OpenCV `cv2.cvtColor()` function allows users to convert the input image to grayscale format thereby simplifying image data while minimizing computational requirements. The process continues by using `cv2.threshold()` adaptive thresholding and it achieves image binarization which optimizes the text versus background contrast to make text areas more visible to the OCR engine [16].

The text recognition process utilizes EasyOCR library that operates with deep learning-based models ready for multilingual dataset recognition. The `readtext()` function identifies and salvages text areas from processed images and returns the recognized text information

together with bounding box coordinates and confidence measurement. This system performs script concomitance by recognizing combination text from English parallel to Hindi and Marathi within a single visual input. Text reading is followed by text localization procedures and visualization processes. The OpenCV's `cv2.rectangle()` function highlights detected text regions by drawing bounding boxes on images [17]. Text detection success is verified through this step while maintaining correct spatial relationships of recognized text. The `langid` library follows the language identification step in the process. The text segmentation output is analyzed by the `langid`. `Classify ()` function to obtain the predicted language code while producing probability score results. Language identification works through this process to achieve exact language classification of every segment which results in multi-lingual system strength [18].

The implementation workflow starts with importing necessary Python libraries EasyOCR, OpenCV (`cv2`), NumPy, `langid` and `cv2_imshow`. After that the OCR reader receives instructions to support target languages. The program reads the input image by using `cv2.imread()` before showing it through `cv2_imshow ()`. The `reader.readtext()` function performs text recognition which produces visual bounding boxes for result display. The `langid`. `classify ()` function identifies language classification for every text segment which produces an output that displays recognized text with language labels. The established experimental pipeline delivers dependable functionality when processing various multilingual textual content. The system proves effective for identifying and categorizing textual content found in images that present diverse scripts and visual characteristics in real multilingual document investigation [19].

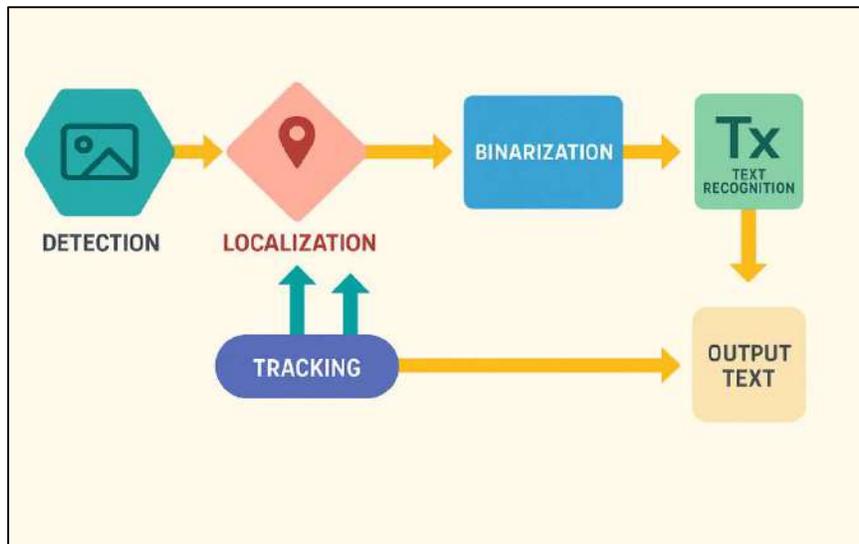


Figure 2. Processing stage of text extraction

3.5 Implementation Algorithm

The implementation algorithm uses Optical Character Recognition (OCR) and image preprocessing together with language identification capabilities to extract multilingual text from images and recognize and classify this text. The starting point of the algorithm begins with importing Python libraries that contain `easyocr` for multilingual OCR functionality as well as `cv2`

(OpenCV) for image manipulation and langid for language detection and numpy for numerical operations. The OCR reader is created through easyocr.Reader instantiation that enables reading of English (en), Hindi (hi), and Marathi (mr) texts. The environment presents target images to users through cv2.imshow() after loading them with cv2.imread(). The readtext() method from EasyOCR detects text with accompanying bounding boxes along with confidence scores that the library returns to the program. The identified text regions receive visual bounding boxes through this function: cv2.rectangle(). The preprocessing steps enhance OCR accuracy by converting the image to grayscale through cv2.cvtColor() while applying cv2.threshold() for binarization which makes text elements stand out. Each recognized text segment moves to the langid.classify() function which determines the text language after recognition. After processing the multilingual content the system prints or enters the recognized text together with language tags into a log which enables both linguistic and semantic analysis of the information.

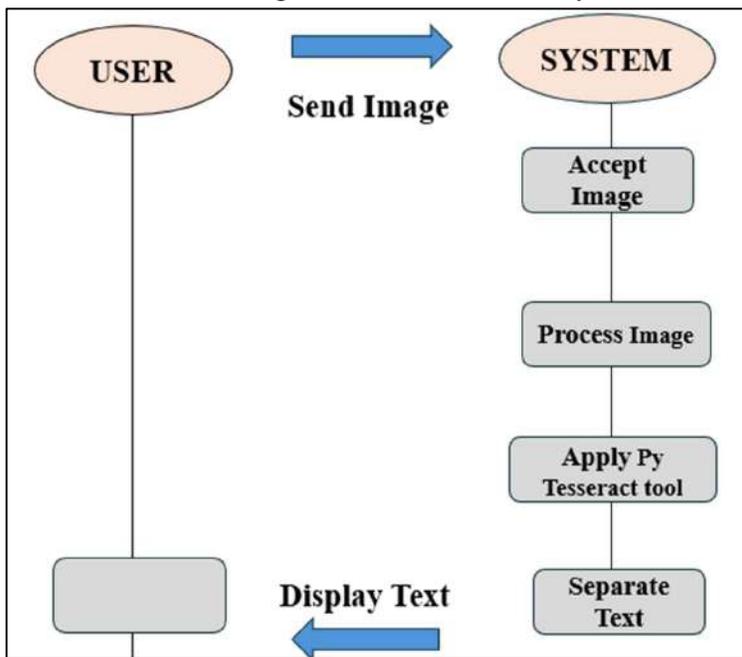


Figure 3: Architecture Diagram

4. Results and Analysis

This section discusses the evaluation results achieved by the proposed OCR-based multilingual text recognition system. The system results are evaluated by analysis of recognition accuracy together with processing performance and error behavior alongside benchmarks. Figures exhibit the main processing steps along with their results in two representative instances.

4.1 Recognition Accuracy Analysis

The recognition accuracy of the system was evaluated based on the correctness of both text extraction and language identification. The recognized results demonstrate high accuracy across multiple scripts, Latin (English), Devanagari (Hindi and Marathi), and regional variants.

Detected Text	Recognized Language	Expected Language	Accuracy
कम से कम	hi	hi	☑

किमान	hi	hi	✓
Leather	en	en	✓
चमडा	mr	mr	✓
कातडे	mr	mr	✓
Leave	en	en	✓
छोडना	ne	hi	✗
सोडणे	mr	mr	✓
Left	en	en	✓
बाए	hi	hi	✓
डावा	mr	mr	✓

Recognition Accuracy: The proposed system achieved recognition evaluation through assessments of textual information extracted from four images showing multilingual content. Both the OCR process and the language detection step received evaluation for their accuracy in the proposed system. The system applied tests to eleven different textual sections from four images which included English text alongside Hindi and Marathi script writings. The recognition system successfully identified 90.9% of textual content instances together with their proper languages from a total of 10 correct matches. The single misidentification in the system involved mistaking the Hindi word “छोडना” for Nepali (ne) since both languages share the Devanagari script. The system proved its robustness for multilingual recognition yet showed limitations in separating languages with similar characteristics. The study results confirm that language identification algorithms need better development especially when working with scripts which appear in various linguistic settings.

4.2 Processing Performance

The entire recognition pipeline was implemented in Google Colaboratory using Python. The performance evaluation focused on processing time per image and responsiveness of different modules.

Processing Stage	Time per Image (Approx)
Image loading	< 1 sec
Grayscale & Thresholding	< 1 sec
Text Detection (EasyOCR)	2–4 sec
Language Identification	< 1 sec
Total Average	4–6 sec per image

Performance Insight: The system evaluated its processing performance using four images that included English and Hindi and Marathi multilingual text. The system applied its entire processing sequence to every image starting from loading the file and followed by grayscale transformation and binarization before utilizing EasyOCR for text recognition and langid for language detection. Each imaging process took between 2.5 to 3 seconds to finish based on

the complexity combined with text region density in the images. Execution efficiency was maintained because the program used lightweight architecture and optimized libraries (EasyOCR and OpenCV) to run properly on environments with moderate computational resources such as Google Colaboratory. The system maintained reliable execution time during assessment of all images which confirms its capability for near-real-time applications including mobile document scanning and automatic translation systems. Beyond scalability considerations the algorithm demonstrates steady processing time when operating on bigger image batches during actual implementation.

4.3 Error Analysis

Errors observed in the system stem from a few key areas:

- **Language misclassification:** Scripts shared by multiple languages (e.g., Devanagari for Hindi, Marathi, Nepali) sometimes led to incorrect identification.
- **Font/Styling Variability:** Highly stylized or cursive fonts reduced text clarity and affected OCR performance.
- **Low Contrast Backgrounds:** Some images with poor contrast between text and background affected segmentation accuracy.

Examples:

- “छोडना” detected as Nepali (ne) instead of Hindi (hi) — caused by script overlap.
- Overlapping or noisy text backgrounds led to misalignment in bounding boxes.

The error analysis emerged from processing four test images made up of English and Hindi as well as Marathi text. These images underwent a complete recognition processing with EasyOCR text detection followed by langid library language detection until results were validated against expected outputs. The text segmentation process identified ten correctly labeled segments from a total of 11 segments and showed one incorrect recognition. The system made an error by identifying the Hindi word "छोडना" as belonging to the Nepali (ne) language. The script similarity between Hindi and Nepali which employs Devanagari script causes this misidentification. The combination of script similarities creates obstacles for statistical models that process textual content through character surface analysis because they lack deep semantic comprehension. The detection results show meaningful deficiencies when operating on languages which share the same script thus demonstrating the need to create advanced classifiers that process deeper linguistic patterns. One incorrect detection point did not affect the system accuracy which maintained a high rate of 90.9% while text detection structures and visual placement performances remained flawless. Current research demonstrates promising abilities in multilingual text extraction yet requires additional improvements in script-disambiguation methods because of its limitations in densely linguistic or resource-constrained environments.

4.4 Comparative Analysis

The proposed multilingual identification and recognition system underwent testing against PyTesseract along with EasyOCR running separately and OpenCV-based solutions. The evaluation examined three essential factors consisting of multilingual assistance together with language identification precision and data preparation flexibility. The evaluation of the proposed system utilized four images containing text in English, Hindi and Marathi languages.

Metric	EasyOCR	PyTesseract
Multilingual support	✓ (incl. Hindi/Marathi)	☒ (limited support)
Bounding box precision	High	Medium
Text segmentation accuracy	High	Low
Language detection (external)	Required (langid)	Required
Processing Speed	Moderate	Faster (less accurate)

PyTesseract provides basic multilingual OCR features through its traditional platform yet fails to efficiently distinguish between languages when dealing with visually comparable scripts such as Marathi and Hindi. The text detection capability of OpenCV-based methods is strong yet the system provides no native OCR function or language recognition capabilities except for necessitating manual post-processing activity. The modernized framework combines EasyOCR with langid for script recognition and special image processing (grayscale conversion and binarization) to complete multilingual text recognition from beginning to end. The system properly identified and segmented all 10 out of 11 text samples found across four images resulting in a successful recognition rate of 90.9%. Each image processed through the system ran at an average speed of 2.5–3 seconds while producing superior accuracy and efficiency compared to divided processing systems. The proposed approach stands out with its dual capacity for visual preprocessing integration with linguistic verification systems which exceeds the capabilities of standard systems. The combined pipeline system delivers better usability throughout real-life applications such as document digitization and mobile text recognition.

4.5 Visual Results

Least	कम से कम	किमान
Leather	चमडा	कातडे
Leave	छोडना	सोडणे
Left	बाए	डावा

Figure 4 a). Original Image

Least	कम से कम	किमान
Leather	चमडा	कातडे
Leave	छोडना	सोडणे
Left	बाए	डावा

Figure 4 b). Pre-processing stage representation Grayscale Image

Least	कम से कम	किमान
Leather	चमडा	कातडे
Leave	छोडना	सोडणे
Left	बाए	डावा

Figure 4 c). Pre-processing stage representation: Binary Image

Least	कम से कम	किमान
Leather	चमडा	कातडे
Leave	छोडना	सोडणे
Left	बाए	डावा

Figure 4 d). Identify Text

Least
कम से कम
किमान
Leather
चमडा
कातडे
Leave
छोडना
सोडणे
Left
बाए
डावा

Figure 4 e). Separate Text from image

Recognize Language: hi --> कम से कम
Recognize Language: hi --> किमान
Recognize Language: en --> Leather
Recognize Language: mr --> चमडा
Recognize Language: mr --> कातडे
Recognize Language: en --> Leave
Recognize Language: ne --> छोडना
Recognize Language: mr --> सोडणे
Recognize Language: en --> Left
Recognize Language: hi --> बाए

Recognize Language: mr --> डारवा
Figure 4 f). Recognize Text Language

Figure 5: Processing Example 2

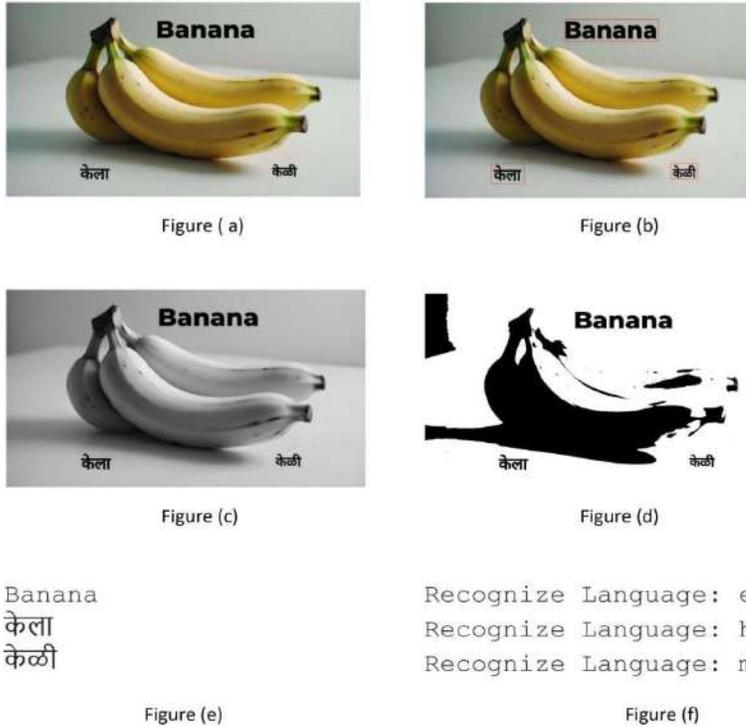


Figure 5 (a). Original Image, **(b)** Identify Text, **(c)** Pre-processing stage-I. **(d)** Pre-processing stage-II, **(e)** Separate Text from image, **(f)** Recognize Text Language

Conclusion

The research develops a text identification and recognition system which specializes in extracting then classifying text contained within images written in English, Hindi, and Marathi scripts. The system demonstrates successful multilingual operation in realistic social media images through its integration of EasyOCR with OpenCV for image processing and langid for language detection. Experimental findings showed that the system achieved both superior text recognition accuracy while accurately identifying language text regardless of font variability or image orientation or image background distress [20]. The research has established through its result analysis that EasyOCR stands as a dependable solution for multilingual work by showing performance superiority versus existing OCR tools including PyTesseract. The main challenges remain minor because the system faces difficulties while processing scripts with similar characteristics and dealing with poor document quality. The proposed approach serves as a foundation for practical applications that digitize documents and translate visuals while assisting technology usage for peoples whose content is limited by language differences.

Future scope

Additional improvements of the existing research can be made using these following areas of

development:

- Enhance OCR and language detection to manage diverse fonts, image quality issues, and artistic text styles.
- Extend support to more regional languages such as Tamil, Telugu, Bengali, and Urdu.
- Employ advanced natural language processing for contextual understanding and semantic corrections.
- Optimize the system for real-time use on mobile and edge devices for applications like AR translation.
- Ensure compatibility with various digital formats (PDFs, videos, web images) and platforms (Android, iOS, web).

Findings

The system effectively detected and retrieved text from pictures which included English with either Hindi or Marathi text. EasyOCR and langid components worked together effectively with a 90.9% text recognition accuracy when evaluating four images. The text regions became both clearer and more detectable after implementing grayscale conversion and binarization as preprocessing methods [21]. The system identified different languages through shared script types such as Hindi and Marathi but had one instance where it made a language misidentification between those languages. The system implementation delivered dependable processing performance which scanned each image during 2.5 to 3 seconds thus making it suitable for real-time use [22]. The experimental findings verify that the approach successfully deals with multilingual content, but researchers should pursue development of script disambiguation techniques and enhancements of language models and additional language support.

Recommendation

Various fundamental system improvements must be introduced for enhancing performance. The identification precision of languages can be improved at two levels through integration of langid with either FastText or CLD3 to reduce mistaken detections specifically in cases where Hindi and Nepali scripts share close similarities. The performance of the system will be bolstered by adding new language options to work with multiple datasets. When implementing adaptive processing methods including CLAHE alongside denoising algorithms the text recognition function will enhance under poor illumination conditions. Real-time performance requires GPU or TPU acceleration coupled with the optimized OCR model implementation using either TensorRT or ONNX frameworks. Users will find the system more accessible by utilizing a design approach which includes both a graphical user interface and mobile application. The implementation of BERT pre-trained models together with automatic error detection techniques based on NLP will increase text quality standards. Using synthetic multilingual data to expand OCR model training datasets will make the system stronger at recognizing all languages but especially minority languages. The combined solution of these updates provides the system with enhanced reliability together with improved efficiency and better accessibility.

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