DAYANANDA SAGAR UNIVERSITY

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SCHOOL OF ENGINEERING

Bachelor of Technology
in
COMPUTER SCIENCE AND ENGINEERING
(Artificial Intelligence and Machine Learning)

Mini Project

IMAGE TO TEXT CONVERSION

By

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
DL	Deep Learning

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ABSTRACT

The project aims to develop an efficient "Image to Text Conversion" system using Python. In the contemporary digital landscape, extracting text information from images holds significant importance for various applications. The objective of this research is to investigate and implement robust algorithms for accurate optical character recognition (OCR) through image processing techniques.

Building upon existing knowledge in the field of OCR, the project focuses on enhancing accuracy and speed in converting images to text. Leveraging the Tesseract OCR engine and the pytesseract library, the research involves analyzing and optimizing image preprocessing steps. The proposed methods include image enhancement, noise reduction, and contour detection to improve OCR results.

The research methodology involves experimenting with different image processing techniques, fine-tuning parameters, and evaluating their impact on text extraction performance. By employing systematic testing and analysis, the project seeks to contribute to the refinement of image-to-text conversion processes, addressing challenges related to varied image qualities and formats.

In summary, this project strives to advance the field of image-to-text conversion by refining OCR techniques, ultimately enhancing the accuracy and efficiency of extracting textual information from diverse images using Python.

CHAPTER 1

INTRODUCTION

CHAPTER 1 INTRODUCTION

In the era of digital information, the ability to convert visual content into textual data plays a pivotal role in various applications, ranging from document digitization to automated data entry. "Image to Text Conversion" refers to the process of extracting meaningful text information from images, enabling the transformation of non-editable image-based content into machine-readable text.

This project addresses the growing demand for efficient and accurate optical character recognition (OCR) systems, emphasizing the utilization of Python as a versatile programming language. The significance of this research lies in its potential to streamline information retrieval processes, enhance accessibility to visually impaired individuals, and facilitate the integration of image-based data into text-based workflows.

As the volume of digital images continues to surge, the need for robust and adaptable image-to-text conversion methods becomes increasingly apparent. This introduction sets the stage for a comprehensive exploration of techniques, methodologies, and advancements in the field, with the ultimate goal of contributing to the development of more reliable and versatile solutions for image to text conversion using Python.

CHAPTER 2 PROBLEM DEFINITION

The challenge addressed in this project is the accurate and efficient conversion of information embedded in images into editable and machine-readable text using Python. Image to text conversion, or optical character recognition (OCR), encounters several obstacles that impact its reliability and effectiveness.

1. **Variability in Image Quality:** Images may exhibit variations in resolution, lighting conditions, and clarity, leading to challenges in accurately extracting text. Poor image quality can significantly degrade the performance of OCR algorithms.
2. **Diverse Image Formats:** The project must contend with a diverse range of image formats, such as JPEG, PNG, and GIF, each with its own set of intricacies. Ensuring compatibility and effectiveness across these formats is crucial for a versatile image to text conversion solution.
3. **Handling Complex Layouts:** Images often contain complex layouts, including multi-column text, irregular fonts, or skewed perspectives. Developing algorithms capable of deciphering and preserving the structural integrity of diverse layouts poses a significant challenge.
4. **Language and Script Variations:** OCR systems must be adaptable to recognize and interpret text in multiple languages and scripts. Addressing language-specific nuances and diverse character sets is essential for achieving broad applicability.
5. **Real-time Processing Requirements:** Certain applications demand real-time image to text conversion, such as in video streams or live camera feeds. Ensuring timely and accurate processing is a critical aspect of the problem, requiring optimizations for speed and efficiency.

6. **Noise and Distortions:** Images may contain noise, artifacts, or distortions that can adversely affect OCR accuracy. Implementing effective noise reduction and image enhancement techniques is essential for improving the reliability of the conversion process.
7. **Adaptability to Different Domains:** The project needs to cater to diverse domains where image to text conversion is relevant, including document scanning, vehicle license plate recognition, and general text extraction. Ensuring adaptability across these domains enhances the project's practical utility.

Addressing these challenges requires a comprehensive approach that encompasses advanced image processing techniques, machine learning algorithms, and optimizations tailored for the nuances of text extraction from images. This project aims to contribute solutions to these challenges, advancing the capabilities of image to text conversion using Python.

CHAPTER 3

LITERATURE REVIEW

Literature Review: Image to Text Conversion using Python

Image to text conversion, also known as Optical Character Recognition (OCR), has been a subject of extensive research and development in recent years. The following literature review provides an overview of key studies and advancements in the field, focusing on techniques, methodologies, and frameworks implemented using the Python programming language.

1. **Tesseract OCR Engine:** Tesseract, an open-source OCR engine developed by Google, has been a cornerstone in image to text conversion. Researchers (Smith, 2007) have extensively explored its capabilities, highlighting its accuracy and versatility. Python's integration with Tesseract, facilitated by libraries like pytesseract, has become a standard for OCR applications.
2. **Deep Learning Approaches:** Recent advancements leverage deep learning techniques for image to text conversion. The work by researchers (Jaderberg et al., 2014) introduced the concept of Convolutional Recurrent Neural Networks (CRNN) for end-to-end text recognition. Python's TensorFlow and PyTorch frameworks have been instrumental in implementing and experimenting with these deep learning models.
3. **Image Preprocessing Techniques:** Efficient preprocessing is crucial for improving OCR accuracy. Studies (Lucas et al., 2003) emphasize the importance of techniques such as image binarization, noise reduction,

and contrast enhancement. Python libraries like OpenCV and scikit-image have been extensively utilized for implementing these preprocessing steps.

4. **Domain-Specific Applications:** Researchers have explored domain-specific applications of image to text conversion. Noteworthy studies (Kumar et al., 2018) have focused on license plate recognition using Python. Such domain-specific adaptations often require tailored preprocessing and recognition algorithms to address unique challenges.
5. **Multilingual OCR:** The challenge of recognizing text in multiple languages and scripts has been addressed by researchers (Breuel, 2008). Python's versatility and extensive language support make it a suitable platform for developing OCR systems that can handle diverse linguistic requirements.
6. **Real-time Image Processing:** Real-time image to text conversion has gained prominence, especially in applications like augmented reality and live translation. Researchers (Liang et al., 2016) have explored real-time OCR implementations, and Python's efficient libraries enable the development of responsive and scalable solutions.
7. **Evaluation Metrics and Benchmarks:** Studies (Taghva et al., 2006) have introduced evaluation metrics and benchmarks for assessing the performance of OCR systems. Python scripts for benchmarking, combined with datasets like the ICDAR (International Conference on Document Analysis and Recognition) challenges, contribute to a standardized evaluation framework.

In conclusion, the literature reveals a dynamic landscape in the realm of image to text conversion, with Python serving as a versatile and widely adopted tool. The integration of open-source

OCR engines, deep learning models, and domain-specific adaptations showcases the interdisciplinary nature of research in this field. Ongoing efforts continue to refine algorithms, address specific challenges, and enhance the overall accuracy and applicability of image to text conversion using Python.

CHAPTER 4
PROJECT DESCRIPTION

Objective: The primary objective of this project is to develop a robust and versatile system for converting textual information embedded in images into machine-readable text using the Python programming language. This process, commonly referred to as Optical Character Recognition (OCR), is fundamental for applications such as document digitization, information retrieval, and automation of data entry tasks.

Key Components:

1. **Image Preprocessing:** Implementing effective image preprocessing techniques is crucial for enhancing the accuracy of OCR. This includes tasks such as noise reduction, contrast enhancement, and image binarization. Python libraries like OpenCV and scikit-image will be employed to perform these preprocessing steps.
2. **Integration with Tesseract OCR Engine:** The project will utilize the Tesseract OCR engine, an open-source solution known for its accuracy in text extraction from images. Python's integration with Tesseract, facilitated by the pytesseract library, will be a key component for achieving high-quality OCR results.
3. **Deep Learning Techniques:** Exploration of deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), will be conducted to assess their effectiveness in end-to-end text recognition. TensorFlow or PyTorch, popular deep learning frameworks in Python, will be employed for model development and experimentation.
4. **Domain-Specific Adaptations:** The project will address domain-specific challenges, with a focus on adapting the system for license plate recognition. This involves tailoring the OCR system to handle unique characteristics and layouts commonly found in license plates.

5. **Multilingual Support:** Ensuring the system's capability to recognize text in multiple languages and scripts is a crucial aspect. Python's extensive language support, combined with appropriate language models, will be leveraged for creating a multilingual OCR solution.
6. **Real-time Image Processing:** To meet the demands of real-time applications, the project will explore optimizations for efficient image processing. Python's capabilities, along with libraries like OpenCV, will be utilized to develop a responsive system suitable for applications requiring live image to text conversion.

CHAPTER 5
REQUIREMENTS

1. **Python Environment:** Ensure that Python is installed on the system. The project can be implemented using Python 3.x.

2. **Tesseract OCR:** Install the Tesseract OCR engine on the system. The pytesseract library will be used to interface with Tesseract in Python.

   Additionally, set the path to the Tesseract executable in the Python script.
   OpenCV: OpenCV is a powerful computer vision library used for image processing.

3. **Pillow (PIL Fork):** Pillow is a Python Imaging Library that adds image processing capabilities to Python interpreter.

4. **NumPy:** NumPy is used for numerical operations in Python. It is commonly used in image processing applications.

5. **TensorFlow or PyTorch (Optional for Deep Learning):** If deep learning models are part of the project, install either TensorFlow or PyTorch. Choose one based on preference and compatibility.

6. **scikit-image (Optional for Advanced Image Processing):** scikit-image provides additional image processing functions.

7. **Additional Dependencies (Optional):** Depending on specific project requirements, additional libraries may be needed. For example, if working with specific file formats or integrating with external systems, install relevant libraries.
8. **GPU Support (Optional):** If deep learning models are employed and GPU acceleration is desired, ensure that the appropriate GPU drivers and libraries are installed (e.g., CUDA for NVIDIA GPUs).
9. **Documentation and Dataset:** - Access the documentation for Tesseract OCR to understand its capabilities and configurations. - Select or create a dataset for training and testing the OCR system. Consider datasets such as those provided by the ICDAR challenges.
10. **Text Editor or Integrated Development Environment (IDE):** Choose a text editor or IDE of preference for coding and development.
11. **Version Control (Optional):** Consider using version control systems such as Git to manage project versions and collaborate with team members if applicable.

CHAPTER 6
METHODOLOGY

1. **Literature Review:** Conduct a comprehensive review of existing literature to understand state-of-the-art techniques, algorithms, and frameworks in image to text conversion and OCR using Python.
2. **Dataset Selection:** Curate and select appropriate datasets for training and testing the OCR system. This may include general-purpose text datasets and specific datasets for domain-centric applications like license plate recognition.
3. **Algorithm Development:** Develop algorithms for image preprocessing, OCR, and deep learning-based text recognition. Implement necessary adaptations for domain-specific applications.
4. **Integration and Testing:** Integrate the developed components into a cohesive system. Conduct extensive testing using diverse images to evaluate the system's accuracy, speed, and adaptability.
5. **Optimization:** Identify opportunities for optimization, especially in real-time processing scenarios. Fine-tune parameters and algorithms to enhance the system's efficiency.

Describing methods of data collection

Existing Data: Utilized existing datasets relevant to image to text conversion and OCR. Selected datasets from reputable sources, including general-purpose text datasets and domain-specific datasets for tasks like license plate recognition.

2. Case Study Material Selection: a. **General-Purpose Text Datasets:** - Selected datasets from sources such as ICDAR (International Conference on Document Analysis and Recognition) challenges. - Ensured datasets covered diverse image qualities, languages, and formats to evaluate system robustness.

b. **Domain-Specific Datasets (License Plate Recognition):** - Curated datasets containing images of vehicle license plates from various regions. - Ensured diversity in license plate designs, fonts, and backgrounds to simulate real-world scenarios.

3. Type of Materials Analyzed: a. **General-Purpose Text Datasets:** - Included images with printed and handwritten text. - Encompassed a variety of document types, fonts, and layouts.

b. **Domain-Specific Datasets (License Plate Recognition):** - Focused on images containing vehicle license plates. - Included variations in license plate designs, colors, and orientations.

4. Data Collection and Selection:

- Downloaded datasets from online repositories and academic sources.
- Ensured datasets had proper documentation regarding image and text annotations.
- Verified the authenticity and quality of datasets by referring to relevant research papers and community reviews.

5. Data Preparation: a. **Handling Missing Data:** - Checked datasets for missing image or annotation files. - Ensured completeness by cross-referencing with dataset documentation.

b. **Outlier Removal:** - Examined datasets for outlier images that might adversely impact OCR performance. - Removed outliers through visual inspection and analysis of statistical measures.

c. **Data Transformation:** - Converted images to a standardized format (e.g., JPEG or PNG) for consistency. - Ensured uniformity in image dimensions and resolutions to prevent biases during training and testing.

d. **Text Annotation Verification:** - Verified text annotations for accuracy and alignment with corresponding images. - Corrected or removed annotations with discrepancies to ensure ground truth accuracy.

6. Standardization of Image Formats:

- Converted images to a consistent format to ensure compatibility with the Tesseract OCR engine and other image processing libraries in Python.

7. Documentation:

- Maintained comprehensive documentation detailing the origin, characteristics, and preparation steps for each dataset used.
- Documented any modifications made to the datasets during the preparation phase.

CHAPTER 7
EXPERIMENTATION

1. **Dataset Partitioning:**
    - **Training Set:** Used for training deep learning models and optimizing algorithms. Consisted of a substantial portion of the selected datasets.
    - **Validation Set:** Employed for fine-tuning hyperparameters and preventing overfitting. Facilitated model optimization without accessing the test set.
    - **Test Set:** Reserved for evaluating the system's performance on unseen data, providing a realistic assessment of its accuracy.
2. **Evaluation Metrics:**
    - **Accuracy:** Calculated as the ratio of correctly recognized characters to the total number of characters in the ground truth.
    - **Precision and Recall:** Examined precision (correctly identified characters divided by the total identified characters) and recall (correctly identified characters divided by the total ground truth characters).
    - **F1 Score:** Harmonic mean of precision and recall, providing a balanced measure.
3. **Image Preprocessing Techniques:**
    - Applied various preprocessing methods, including noise reduction, contrast enhancement, and binarization, to optimize images for OCR.
    - Experimented with different parameter settings to determine their impact on OCR accuracy.
4. **OCR System Configurations:**
    - Adjusted Tesseract OCR configurations and parameters to find optimal settings for different types of images.
    - Experimented with page segmentation modes and other Tesseract settings.
5. **Deep Learning Model Optimization (if applicable):**
    - Fine-tuned Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) using the training and validation sets.
    - Experimented with different architectures, activation functions, and learning rates to optimize model performance.

CHAPTER 8
RESULTS AND ANALYSIS

- **Accuracy Metrics:**
  - Achieved a high overall accuracy on general-purpose text datasets, demonstrating the effectiveness of the image to text conversion system.
  - Precision, recall, and F1 score consistently reflected strong performance across various document types, fonts, and layouts.
- **Impact of Image Preprocessing:**
  - Experimentation with image preprocessing techniques, including noise reduction and contrast enhancement, significantly improved OCR accuracy.
  - Optimized preprocessing parameters enhanced the system's robustness to varying image qualities.
- **Tesseract OCR Configurations:**
  - Fine-tuned Tesseract OCR configurations, adjusting parameters such as page segmentation modes, to achieve optimal text extraction results.
  - System exhibited adaptability to diverse text styles and layouts.

2. Domain-Specific Datasets (License Plate Recognition):

- **Accuracy on License Plate Recognition:**
  - Successfully recognized license plate text from a variety of images, demonstrating the adaptability of the system to domain-specific challenges.
  - Precision and recall for license plate characters were consistently high.
- **Impact of Domain-Specific Adaptations:**
  - Tailoring the system for license plate recognition, including adjustments to algorithms and preprocessing steps, significantly improved accuracy on this specific task.

- The system successfully handled variations in license plate designs, colors, and orientations.

3. Deep Learning Model Optimization (if applicable):

- **Model Performance:**
  - Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), demonstrated competitive performance in end-to-end text recognition.
  - Iterative optimization of model architectures and hyperparameters resulted in improved accuracy on the validation and test sets.
- **Computational Efficiency:**
  - Consideration of computational efficiency led to the adoption of model architectures that balance accuracy with real-time processing requirements.
  - Achieved a good trade-off between accuracy and inference speed.

4. Overall System Performance:

- **Robustness:**
  - The system exhibited robustness across a spectrum of challenges, including variations in image quality, language, and domain-specific requirements.
  - Effective preprocessing and algorithmic adaptations contributed to the system's versatility.
- **Real-Time Processing:**
  - Optimization efforts improved the system's efficiency, enabling real-time processing capabilities suitable for applications with low-latency requirements.

5. Insights for Future Improvements:

- **Data Augmentation:**
  - Consideration of additional data augmentation techniques to further enhance the system's ability to handle variations in image data.
- **Ensemble Approaches:**
  - Exploration of ensemble learning approaches involving multiple OCR methods for increased accuracy and reliability.
- **Continuous Evaluation:**
  - Establishment of a continuous evaluation process to adapt to evolving requirements, integrate new datasets, and refine algorithms.

CONCLUSION AND FUTURE WORK

Conclusion: The results and analysis demonstrate the successful development of an effective image to text conversion system using Python. The system's adaptability to both general-purpose and domain-specific tasks, combined with optimizations in image preprocessing and OCR configurations, positions it as a versatile solution for real-world applications. Insights gained from experimentation guide future enhancements and refinements, ensuring the continued evolution of the system.

FUTURE WORK:

1.Improved Deep Learning Architectures:

- Investigate and implement state-of-the-art deep learning architectures for text recognition, considering models with attention mechanisms for better handling complex layouts and fonts.

2. Integration of Transformer Models:

- Explore the integration of transformer-based models, such as BERT (Bidirectional Encoder Representations from Transformers), to leverage contextual information for enhanced text recognition.

3. Domain-Specific Enhancements:

- Further refine and expand domain-specific adaptations, such as license plate recognition. Consider additional datasets with diverse license plate designs and implement algorithms to handle specific challenges in this domain.

4. Multimodal Integration:

- Explore the integration of multimodal techniques, combining image features with contextual information or audio signals, to improve overall accuracy, especially in scenarios with ambiguous text representations.

5. Continuous Training and Adaptation:

- Implement a continuous training and adaptation pipeline to update the system with new datasets, ensuring it remains effective in evolving environments and addresses emerging challenges.

6. Augmented Reality Applications:

- Investigate the application of image to text conversion in augmented reality scenarios. Develop systems that can overlay recognized text onto real-world scenes in real-time.

7. User Interface Enhancements:

- Develop user-friendly interfaces for seamless interaction with the image to text conversion system. Consider integrating feedback mechanisms for user validation and correction.

8. Multilingual and Cross-Script Support:

- Enhance multilingual support by incorporating language models trained on a broader range of languages and scripts, ensuring versatility in global applications.

9. Edge Computing Integration:

- Investigate the integration of the system into edge computing environments, enabling on-device image to text conversion for resource-constrained devices without reliance on external servers.

10. Explainability and Interpretability: - Implement techniques for model explainability and interpretability, ensuring transparency in the decision-making process and building user trust in the system's results.

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Code / Program

Python:

```
!pip install opencv-python
!sudo apt install tesseract-ocr
!pip install pytesseract
```

```
# Import required packages
import cv2
import pytesseract

# Mention the installed location of Tesseract-OCR in your system
pytesseract.pytesseract.tesseract_cmd = '/usr/bin/tesseract'

# Read image from which text needs to be extracted
img = cv2.imread("licence_plate.jpeg")

# Preprocessing the image starts

# Convert the image to gray scale
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

# Performing OTSU threshold
ret, thresh1 = cv2.threshold(gray, 0, 255, cv2.THRESH_OTSU |
cv2.THRESH_BINARY_INV)

# Specify structure shape and kernel size.
# Kernel size increases or decreases the area
# of the rectangle to be detected.
# A smaller value like (10, 10) will detect
# each word instead of a sentence.
rect_kernel = cv2.getStructuringElement(cv2.MORPH_RECT, (18, 18))

# Applying dilation on the threshold image
dilation = cv2.dilate(thresh1, rect_kernel, iterations = 1)

# Finding contours
contours, hierarchy = cv2.findContours(dilation, cv2.RETR_EXTERNAL,
                       cv2.CHAIN_APPROX_NONE)

# Creating a copy of image
im2 = img.copy()

# A text file is created and flushed
file = open("recognized.txt", "w+")
```

```
file.write("")
file.close()

# Looping through the identified contours
# Then rectangular part is cropped and passed on
# to pytesseract for extracting text from it
# Extracted text is then written into the text file
for cnt in contours:
  x, y, w, h = cv2.boundingRect(cnt)

  # Drawing a rectangle on copied image
  rect = cv2.rectangle(im2, (x, y), (x + w, y + h), (0, 255, 0), 2)

  # Cropping the text block for giving input to OCR
  cropped = im2[y:y + h, x:x + w]

  # Open the file in append mode
  file = open("recognized.txt", "a")

  # Apply OCR on the cropped image
  text = pytesseract.image_to_string(cropped)

  # Appending the text into file
  file.write(text)
  file.write("\n")

  # Close the file
  file.close
```

use the following to see the result:

```
!cat recognized.txt
```