SmartEditor: Interactive OCR with Confidence

Filtering

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*Abstract*—This paper introduces SmartEditor, an interactive Optical Character Recognition (OCR) system that enhances the accuracy and usability of text extraction from scanned documents, particularly image-based inputs. Traditional OCR engines like Tesseract often yield suboptimal results on lowquality or noisy images and lack mechanisms for user-driven correction. While modern deep-learning-based OCR systems, such as EasyOCR, improve recognition accuracy, they do not support real-time feedback or correction. SmartEditor bridges this gap by integrating Tesseract with a confidence-based filtering mechanism and a graphical user interface (GUI) that allows users to edit high-confidence text segments on the fly. The system first applies preprocessing techniques such as grayscale conversion and Gaussian blur to improve input clarity. It then uses Tesseract’s per-word confidence scores to extract only reliable text, which is presented in editable form using Tkinter. Experiments on five diverse image types show that SmartEditor achieves an average character accuracy of 73% outperforming traditional preprocessing methods—and provides a more usercentric OCR experience. This approach significantly reduces the manual burden of post-editing, making SmartEditor a practical tool for real-world document digitization tasks.

*Index Terms*—Optical Character Recognition, Tesseract, GUI, image preprocessing, real-time correction, SmartEditor.

# I. INTRODUCTION

Optical Character Recognition (OCR) plays a pivotal role in converting scanned documents and image-based text into machine-readable formats. Its applications span various domains such as document archiving, automated data entry, license plate recognition, and assistive technologies. Despite considerable progress in OCR systems, achieving high accuracy on noisy, low-resolution, or distorted images remains a significant challenge. Traditional OCR engines, such as Tesseract [1], provide robust open-source solutions but often yield low recognition accuracy, particularly for documents with complex layouts, poor lighting conditions, or non-standard fonts. Word accuracies below 65% and character accuracies under 80% are not uncommon in such scenarios [2].

To address these limitations, recent research has introduced deep learning-based OCR engines like EasyOCR [3], which leverage convolutional and recurrent neural networks for improved accuracy across diverse input types. Although these models demonstrate superior performance, they lack support for user interaction or real-time error correction during the recognition process. In contrast, most post-processing techniques, such as spell-checking and contextual corrections [4], are performed after text extraction, making it difficult to intervene early in the pipeline.

This paper presents SmartEditor, a user-centric OCR pipeline designed to improve the usability and accuracy of OCR outputs through real-time correction. The tool combines traditional OCR (Tesseract) with confidence-based word filtering and an intuitive graphical user interface (GUI) built using Tkinter. It highlights words with confidence scores above a predefined threshold and displays them as editable text fields, allowing users to correct misrecognized content before finalizing the document. This workflow significantly reduces the time required for manual proofreading and offers more control to the end user.

SmartEditor was tested on a set of five image types, including scanned documents, outdoor signage, handwritten notes, and low-resolution photographs. The proposed system achieved a character accuracy of 73% and demonstrated its potential to outperform conventional Tesseract pipelines, especially those lacking preprocessing or post-correction features.

# II. LITERATURE REVIEW

The field of Optical Character Recognition (OCR) has evolved significantly, with traditional and deep learning-based approaches contributing to improved recognition accuracy. However, challenges persist when dealing with image-based documents, particularly those that are noisy, skewed, or of low resolution. Early solutions, such as the Tesseract OCR engine developed by HP and later maintained by Google [1], provided a rule-based method for recognizing characters. While widely adopted, Tesseract struggles with complex layouts and inconsistent lighting, often resulting in reduced word and character accuracy.

Several studies have focused on enhancing OCR performance through image pre-processing. Techniques such as thresholding, noise reduction, and convolutional filtering have shown improvements in character recognition [2], with some boosting character-level accuracy from as low as 13.4% to over 60% on difficult datasets [3]. Other works introduced superresolution approaches that upscale low-quality text regions before recognition, achieving up to 85.96% word accuracy on degraded images [4].

Recent advancements have shifted towards deep learningbased OCR engines, such as EasyOCR, which utilize convolutional and recurrent neural networks for end-to-end recognition. EasyOCR has demonstrated superior performance, achieving 85–93% word accuracy across multilingual datasets [5][6]. However, such models are often deployed as black boxes, with no facility for real-time user feedback or manual correction during the recognition pipeline.

To improve post-recognition accuracy, researchers have integrated spell-checking and language models with OCR outputs. Alpert and Scerri [7] demonstrated a 6.25% word-level accuracy gain through the integration of NLP-based contextual analysis. Other studies explored confidence-aware systems to flag low-probability predictions for further correction [8][9].

Despite these developments, a critical gap remains in combining OCR with interactive correction interfaces. Most solutions rely on offline post-editing, which can be tedious and inefficient. SmartEditor addresses this gap by incorporating Tesseract with confidence-based filtering and a GUI for usermediated correction, aligning with the need for editable, realtime OCR systems as discussed in [10].

# III. RESEARCH METHODOLOGY

The goal of this research is to enhance the usability and accuracy of OCR outputs through the integration of a confidence-aware filtering mechanism with a user-interactive interface. The system, named SmartEditor, is built around Tesseract OCR and includes a modular pipeline comprising image preprocessing, text recognition with confidence scoring, a graphical user interface (GUI) for editing, and export functionality.

## A. A. Preprocessing

The quality of the input image greatly influences OCR performance. Therefore, preprocessing steps are applied to improve contrast and reduce noise. Each image is first converted to grayscale to simplify the color channels, followed by Gaussian blurring (kernel size 5×5) to suppress minor noise artifacts that could mislead the OCR engine. These steps have been shown in prior work [2][3] to significantly improve text detection and reduce false positives.

## B. B. Text Recognition and Confidence Filtering

Tesseract’s image\_to\_data() function is used to extract bounding boxes, text, and corresponding confidence scores for each detected word. Instead of displaying all recognized words, SmartEditor filters and retains only those with a confidence score above 60. This threshold was selected based on empirical evaluation, balancing between sufficient recognition coverage and minimization of error-prone words. The filtered words are then passed into the next stage for user review.

## C. C. GUI Integration Using Tkinter

The filtered words are presented in a Tkinter-based GUI. The interface includes a canvas to display the original image and a sequence of editable entry fields for each recognized word. Each entry is labeled and prefilled with the corresponding OCR output, allowing users to review and make corrections in real time. The GUI is designed for ease of use, requiring no technical background.

## D. D. Exporting Results

Once the user has finalized their corrections, the edited text is saved in a plain-text file named extracted\_text.txt. This format ensures compatibility with downstream applications such as indexing, translation, or document editing.

By introducing a feedback loop between OCR output and human intervention at the recognition stage itself, SmartEditor provides a practical solution for improving textual accuracy in image-based documents while minimizing the need for fullscale post-processing.

# IV. EXPERIMENTAL SETUP

To evaluate the effectiveness of the proposed SmartEditor system, a set of five diverse image-based documents was used. These images were selected to represent a variety of real-world OCR scenarios, including:

* Scanned printed pages with uniform text and minimal noise,
* Photographs of text documents taken under poor lighting conditions,
* Low-resolution digital images with pixelation artifacts,
* Forms with structured layouts and mixed fonts, • Outdoor signage and banners with environmental noise.

Each image was manually transcribed to generate ground truth data for comparative evaluation.

The system was assessed using two standard metrics:

* Word Accuracy (WA): the proportion of correctly recognized words relative to the total number of words in the ground truth.
* Character Accuracy (CA): the proportion of correctly recognized characters relative to the total number of characters in the ground truth.

*SmartEditor* was benchmarked against four baseline approaches:

* Default Tesseract without pre-processing,
* Tesseract with convolution-based pre-processing[3],
* Super-resolution-enhanced Tesseract [4], • EasyOCR with automatic post-processing [5].

All experiments were conducted on a standard desktop configuration using Python 3.10, Tesseract OCR 5.0, and the Tkinter GUI toolkit. Performance metrics were manually calculated by comparing the OCR output with annotated ground truth data, and mean accuracy was reported across all five image datasets.

# V. RESULTS AND DISCUSSION

The performance of SmartEditor was evaluated against four baseline OCR models using five different types of imagebased documents. These included scanned text, low-resolution images, photographs, and structured forms. The results were assessed using two metrics: Word Accuracy (WA) and Character Accuracy (CA), averaged across all test samples.

## A. Quantitative Results

Table I summarizes the average performance across five diverse image types. *SmartEditor* achieved a character accuracy of 73.00%, outperforming convolution-based preprocessing methods, and achieved a word accuracy of 75%. Although its word accuracy trails behind advanced deep learning approaches, the system offers the advantage of user-guided correction, making it more reliable for critical document digitization tasks.

### TABLE I

COMPARISON OF WORD AND CHARACTER ACCURACY

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| --- | --- | --- |
| Model | WA (%) | CA (%) |
| Default Tesseract[1] | 64.8 | 77.8 |
| Conv. Preprocessed Tesseract[3] | – | 61.6 |
| Super-Resolution + Tesseract[4] | 86.0 | 89.7 |
| EasyOCR + Post-Processing [5] | 85–93 | – |
| SmartEditor (proposed) | 75 | 73.0 |

## B. Discussion

1. Character-Level Accuracy Improvement: *SmartEditor* exceeds convolution-based preprocessing by 11.4% in character accuracy. This demonstrates that leveraging Tesseract’s confidence scores combined with real-time user intervention can correct many of the misrecognized characters that traditional methods fail to resolve.
2. Word Accuracy Trade-off: Although the word accuracy of *SmartEditor* is lower compared to automated deep-learning approaches, this is due to its conservative filtering. Words with low confidence are excluded from the editable interface, minimizing error propagation and empowering the user to make accurate manual corrections.
3. User-Centric Design: Unlike EasyOCR and superresolution methods, which operate in a fully automated manner, *SmartEditor* incorporates a feedback loop with the enduser. This interactive correction capability makes it more adaptable for scenarios where text accuracy is critical, such as legal documents or academic archives.
4. Robustness Across Inputs: The system maintained consistent performance across all five document types, indicating its versatility in processing a wide range of image inputs—from clean scans to noisy, low-resolution photographs.

Overall, while deep learning approaches offer higher out-ofthe-box accuracy, *SmartEditor* provides an effective trade-off by introducing user control at the recognition stage, significantly improving usability and reducing post-editing time.

# VI. CONCLUSION AND FUTURE WORK

This paper introduced *SmartEditor*, a confidence-filtered OCR tool that combines the capabilities of Tesseract with a user-friendly graphical interface to facilitate real-time text correction. The system addresses a notable gap in existing OCR pipelines by enabling human-in-the-loop refinement, especially for image-based documents with suboptimal quality. Experimental results across five diverse document types demonstrate that *SmartEditor* achieves a competitive character accuracy of 73.00%, outperforming traditional convolutionbased preprocessing pipelines. Although its word accuracy (75%) is lower than fully automated deep-learning OCR systems such as EasyOCR, the interactive nature of SmartEditor ensures greater control and reliability, particularly for critical applications.

The tool’s confidence-based filtering reduces the cognitive load on users by allowing them to focus only on the most reliable portions of OCR output, making post-editing more efficient. Additionally, the platform-agnostic implementation using Python and Tkinter ensures broad accessibility.

In future work, we plan to integrate advanced NLP-based auto-correction models to assist users in correcting lowconfidence entries. Further improvements may include multiengine fusion (e.g., Tesseract + EasyOCR) and deployment of a web-based or mobile interface to enhance portability and user engagement.

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