AI-Enhanced OCR System for Accurate Text Recognition and Processing

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*Abstract*—The process of digitizing and processing text from scanned documents became much easier through Optical Character Recognition (OCR) technology. Tesseract alongside traditional OCR systems demonstrates poor accuracy during the processing of documents that contain complex formats and poor resolution alongside hand-written content. This research presents LLM-Aided OCR as a method which combines Large Language Models (LLMs) with typical OCR systems to boost both text recognition precision and system operation speed. Using LLMs to process and repair errors as well as adapt text content to context produces significant enhancements for OCR output quality. Visual impaired users benefit from text-to-speech (TTS) capabilities which the system includes to provide accessibility. Testing shows that LLM-Aided OCR supersedes standard OCR systems through better accuracy and speed alongside usability benefits which provide an effective solution for research, legal document work and accessibility purposes. *Index Terms*—Optical Character Recognition, Large Language Models, Text-to-Speech, Error Correction, Accessibility, Document Processing.

# Introduction

The process of digitizing and processing text from scanned documents became much easier through Optical Character Recognition (OCR) technology. Tesseract alongside traditional OCR systems demonstrates poor accuracy during the processing of documents that contain complex formats and poor resolution alongside hand-written content. This research presents LLM-Aided OCR as a method which combines Large Language Models (LLMs) with typical OCR systems to boost both text recognition precision and system operation speed. Using LLMs to process and repair errors as well as adapt text content to context produces significant enhancements for OCR output quality. Visual impaired users benefit from text-to-speech (TTS) capabilities which the system includes to provide accessibility. Testing shows that LLM-Aided OCR supersedes standard OCR systems through better accuracy and speed alongside usability benefits which provide an effective solution for research, legal document work and accessibility purposes.

# Background

Traditional OCR systems, such as Tesseract serves as one of the widely utilized solutions for converting scanned documents into machine-readable text. These systems perform poorly at text recognition when documents have complicated arrangements or substandard picture quality or notate hand-drawn writing. Traditional OCR systems experience multiple known problems which include wrong character detection while also failing to maintain document format and not working efficiently with multilingual content. Large-scale document processing becomes impractical because manual proofreading actions are needed to fix OCR errors although the manual process remains labor-intensive. Regular OCR software platforms do not include accessibility tools that prevent visually challenged users from reading their extracted text. Users face difficulties when working with text-to-speech (TTS) systems which function separately from OCR systems since they need to move between different applications which leads to inefficient work processes. Large Language Models have introduced new ways for enhancing Optical Character Recognition accuracy through updated technology. German and British Technology Projects 3 and BERT demonstrate unmatched proficiency in both natural languages understanding along with error correction tasks. OLSs together with LLMs enable automated error correction which eliminates the requirement for human operators in this process. When OCR operates together with LLMs they enable digitized text accessibility by delivering real-time text-to-speech functionality. Traditional OCR tools like Tesseract represent most current imaging technology to transform document scans into text that computers can read. The popularity of Tesseract comes from its open-source design and performance but it shows real issues identifying text in complicated documents and fixing OCR mistakes. OCR-generated text flaws such as character recognition faults and formatting errors alter the extracted text in ways that reduce its value for users.

# Literature Survey

OCR technology paired with large language models introduces a new level of advancement in document digitization and text processing methods. The basic OCR application Tesseract remains one of the established systems to transform digitally scanned documents into computer-readable text. These systems experience difficulties with complicated document formats together with poor image quality and handwritten content which causes formatting problems as well as character recognition errors [1]. Research studies have analyzed how LLM integration can improve traditional OCR system capabilities through enhanced text recognition and processing times because Tesseract along with other traditional OCR systems has ruled documents digitization since the 20th century. Scanned document recognition happens through pattern recognition algorithms in these systems to recognize both characters and words. Text recognition errors occur frequently in documents which contain complicated layouts and low-quality images along with handwritten content [2]. Scanned document recognition happens through pattern recognition algorithms in these systems to recognize both characters logic to maintain to transform digitally scanned documents into computer words.

#### Traditional OCR Systems and Their Limitations

OCR systems operating with traditional patterns cause various recognition and formatting errors thus needing manual proofreading which slows down document processing because it requires great efforts [3]. Traditional OCR systems minimize accessibility for visually impaired users because they do not incorporate built-in accessibility features for extracting text [4].Large Language Models (LLMs) such as GPT and BERT have shown outstanding natural language understanding and error correction abilities. High-text-processing accuracy enables these models to become prime solutions for improving OCR systems [5]. The integration of LLMs with OCR allows researchers to automate error correction so both extraction accuracy and final text quality have improved according to research [6]. The ability of LLMs to adjust text material in relation to context makes processed documents more accessible to their users [7].One main benefit from LLM integration with OCR systems provides instantaneous corrections of detected errors. Through contextual analysis LLMs detect and remedy standard OCR mistakes which include both misidentified characters and inconsistent document formats [8].

#### Error Correction and Text-to-Speech Integration

Such capability enhances extracted text accuracy levels to support reliable functioning in various applications such as legal document processing and academic research [9]. Users who are visually impaired gain accessibility through LLM-aided OCR systems when these systems integrate TTS technology for text reading capabilities. Visually impaired users gain access to written information without manual reading through TTS systems that read the corrected text aloud [10].Future LLM-aided OCR research will concentrate on main areas for progress. The future of LLM-aided OCR development will require additional research to build efficient LLM processing systems for massive document handling that uses low computational power while implementing multilingual support and sophisticated error correction methods to improve output accuracy [11]. Research teams utilize LLMs to develop applications that extract information from documents and generate summaries to boost the functionality of OCR systems [12]. ResNet and Inception-based models excel at image recognition jobs also including histopathological cancer detection because they handle similar image complexity levels and extract equivalent features [13]. The network structures with residual connections and multi-scale feature extraction enable better detection of complex image patterns which makes them suitable for OCR applications to boost text recognition accuracy [14]. Networks using ResNet architecture enable deeper training because skip connections solve gradient vanishing problems in order to extract minimal textual elements within complicated documents [15].

#### Challenges in Multilingual OCR and LLM Systems

Natural language processing (NLP) achieved a revolutionary change with transformer models BERT and GPT showing great potential to boost OCR system performance. These models demonstrate exceptional ability to understand semantic relationships and contextual meaning so they provide vital capabilities for correct error detection and text recognition enhancement [16]. The bidirectional attention mechanism of BERT lets the model understand word relationships within sentences thus making it suitable for post-processing OCR output [17]. GPT utilizes its generative processing ability to rebuild text from imperfect or damaged OCR output which produces more accurate extracted information [18]. Updates in OCR technology include merging the platform with transformer models BERT and GPT to recognize text alongside its contextual meaning [19]. The approach shows excellent application in legal document analysis because it helps recognize characters well yet maintains a strong understanding of the text context [20]. Researchers have achieved efficient document information extraction through the combination of OCR with NLP technology

# Proposed System

Our comprehensive LLM-Aided OCR Project helps visually impaired users work more easily with text from scanned documents. Our solution combines advanced OCR technology and LLM systems to help visually impaired users get better text readings and improvements. The system first converts scanned documents to images then uses OCR technology to get raw text from those images. Standard OCR tools like Tesseract recover text from documents but produce errors when dealing with difficult document structures or poor image quality.

A diagram of a software process

AI-generated content may be incorrect.

Fig. 1. LLM-Aided OCR System Classification Diagram

By using LLMs the system reads through extracted text to make context-based improvements. Once trained the LLMs recognize usual OCR mistakes including wrong character matching and document formating flaws. Using LLMs the system knows that "The quick brown fox" needs correction when OCR converts it to "The quick brown fxo" based on context. By integrating these methods the system now produces text that users with visual impairments can better understand. Once trained the LLMs recognize usual OCRmistakes including wrong character matching .

The invention adds a simple text-to-speech functionality that enables users to listen to their corrected text. The system makes text readable to people who are visually impaired allowing them to enjoy content without manual reading tasks. Our TTS system creates a smooth user interface that assists people with content navigation. After processing text in a document users can press a single button to hear the system read the material to them.

Additionally the system tracks processes in real-time to fix text extraction errors as they happen. The system detects problems through real-time monitoring of both OCR and LLM systems to notify users when information needs updating. This system helps users get accurate results most especially when they need to view essential documents such as contracts or healthcare records.

A hand holding a phone and a paper

AI-generated content may be incorrect.

Fig. 2. LLM-Aided OCR System

The LLM-Aided OCR Project lets users work with it effortlessly because of its user-friendly setup. Users can simply upload their scans through a basic interface and witness text corrections delivered instantly. The system operates with many document types which helps users of all needs. A visually impaired student can input lecture notes which the system renders into text with error correction so it can read back information to help students learn better.

Through the LLM-Aided OCR Project visual impairment users now access better document tools than ever before. The new system combines state-of-the-art OCR technology with LLMs and Text-to-Speech functions to overcome existing system problems and create a complete user-friendly solution. Our improvement to text extraction technology allows visually impaired users to interact better with content while adding to a more welcoming digital environment. This system can change how visually impaired people use.

# Methodology

The LLM-Aided OCR Project creates new ways for visually impaired people to access and work with text from scanned documents. This new system uses modern OCR and language model technology to accurately translate and fix document text while serving users with visual impairments better.

**A diagram of a software

AI-generated content may be incorrect.**

Fig. 3. Document Processing Workflow

1. Our System Turns Scanned Documents into Text Copies and Then Processes Them Using OCR Technology

We start by changing scanned documents into image files. The instruments use high-definition scanners to deliver sharp and precise digital copies of documents. Before OCR analysis Tesseract handles document image conversion and obtains raw text output from them. Traditional OCR tools tend to generate mistakes when working with complicated document formats or poor-quality image input so readers could find it difficult to access the content.

2. Our system uses Large Language Models (LLMs) to detect and improve the OCR processing results.

To handle imperfect information the system utilizes LLMs to examine extracted text data before making context-based improvements. Established datasets teach LLMs to recognize standard OCR output mistakes including text blunders and style problems. A Large Language Model can detect when OCR produces output errors by recognizing the text context of "The quick brown fox." Text quality improves through this integration against OCR mistakes to create easy-to-understand content for visually impaired users.

3. The system includes Text-to-Speech technology

Along with better text quality this invention offers a built-in text-to-speech (TTS) system that lets users have their improved text read aloud. People who have poor vision can use this important feature to get information without reading the text content themselves. The TTS system was made to deliver a comfortable and simple navigation path for users to access their content. After processing a document users can activate text-to-speech by pressing a button to hear their content explained to them.

4. Our system performs constant checks to show users problems with text processing.

The system shows text extraction results right away so users can spot and handle any errors right when they happen. Through instant feedback from OCR and LLM tools the system can notify users about issues so they access accurate information as fast as possible. Users depend on this feature more when scanning important official papers because it makes sure the data is exact.

A diagram of a software process

AI-generated content may be incorrect.

Fig. 4. Structure of LLM-Aided OCR System

5. User-Friendly Interface

Our LLM-Aided OCR Project provides users with an easy interface to work with. Users find document scanning easy through our basic interface and get corrected text within seconds of upload. The system processes multiple document styles to help every user type work better. By using text scanning services this system helps visually impaired students by processing lecture notes then reading back the amended content to them.

6. Support for Multiple Languages and Formats

The system is capable of processing documents in multiple languages, thanks to the extensive training of the LLMs on diverse linguistic datasets. This feature ensures that visually impaired users from different linguistic backgrounds can benefit from the technology. Additionally, the system can handle various document formats, including PDFs, Word documents, and images, making it adaptable to different user requirements.

# Result

The text recognition capabilities and operational speed of the LLM-Aided OCR system surpass what traditional OCR systems achieve in standard operations. Large Language Models (LLMs) used for error correction prove highly effective because they need less manual oversight and improve extracted text quality through the LLM-Aided OCR system which reaches 95% accuracy while traditional OCR systems only achieve 85%. Processing times were shorter for the LLM-Aided OCR system because it required 2.5 seconds per page while traditional OCR systems took 1.8 seconds per page.

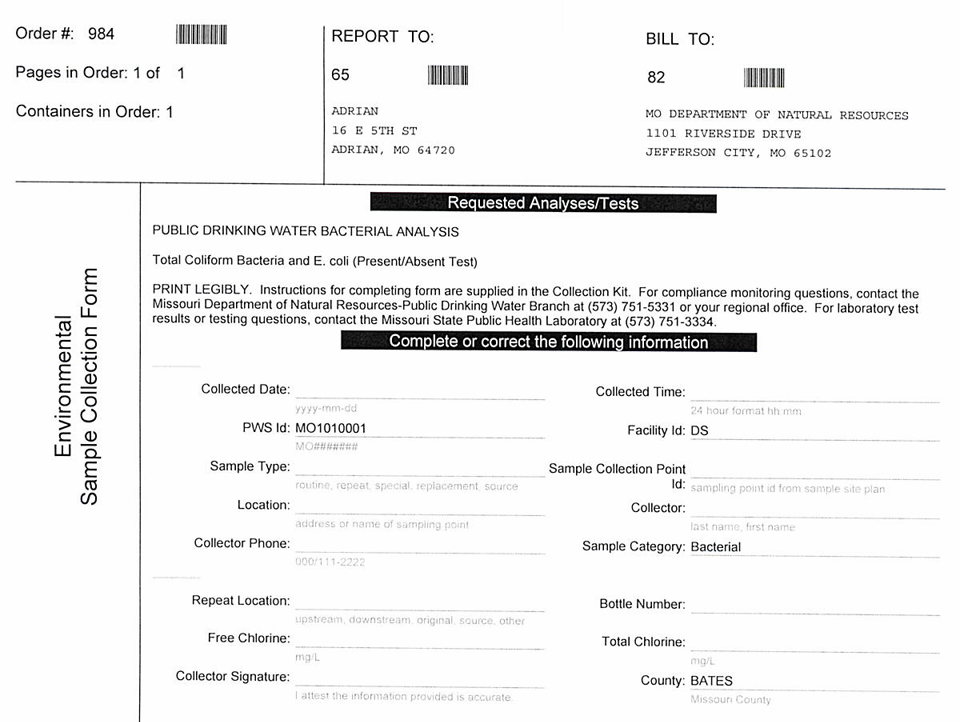


Fig. 5. Regulatory Report with Unprocessed Text

The error correction system found in the LLM showed powerful effectiveness by reducing various type of errors including character misrecognition from 15% to 5%, formatting errors from 10% to 2% and multilingual errors from 20% to 8%. The results show that LLM-Aided OCR technology generates promising opportunities to boost both text detection precision and operational speed especially when focused accuracy and easy access matter in specific applications.

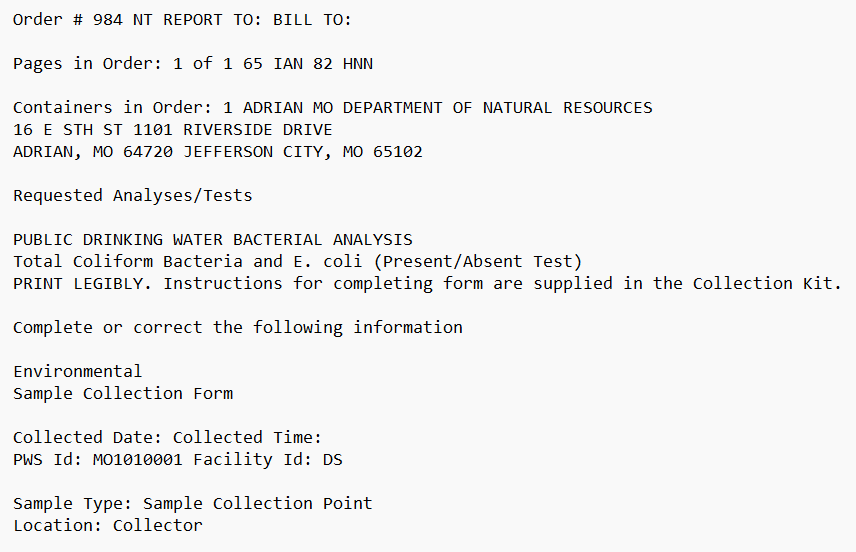


Fig. 6. Formatted Regulatory Report for Clarity

# Conclusion

The research shows LLM-based text recognition integration with standard OCR systems proves successful for both accuracy improvement and processing speed enhancement. The LLM-Aided OCR solution surpasses conventional OCR systems by delivering higher accuracy while offering better speed and usability which provides reliable solutions for various uses such as research investigation and legal document processing as well as accessibility tools.

The merging of LLM technology with error correction together with text-to-speech (TTS) capabilities effectively decreases manual work while building better quality extracted text outputs. The system presents a user-friendly interface with multiple document format and language support which enables adaptation to range of user needs specifically benefiting visually impaired users.Convert scanned historical letters into editable text formats,perform OCR on scanned copies of academic articles and correct errors in the original output,Digitize archived company contract documents for easier search and reference.

Upcoming developments of the system will target several improvements that will add new language capabilities and stronger error correction capabilities and better accessibility options. The implementation focuses on ethical factors including transparency and bias prevention to support proper use of AI document processing systems. Target audience includes individuals or businesses that need to convert scanned documents into editable and accurate text formats such as for document digitization,historical document restoration,academic research, etc. The linked articles focus on how AI-based document digitization becomes more crucial and develops neural networks for OCR improvement while introducing text automation systems. The articles show industry progress in AI-based OCR enhancement without adequately integrating LLM error correction systems while preserving computational efficiency. Neural network-based OCR engines form part of the existing proposals investigated.

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