Technical Report: Invoice Data Extraction System

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Model 1:Invoice Data Extraction System

Introduction

A detailed overview of the first experiment model a Streamlit-based invoice data extraction system designed for processing PDF invoices. The system aims to extract critical invoice information while ensuring high accuracy and trustworthiness of the data.

Libraries Used

- **Streamlit**: Provides a web interface for user interaction and data presentation.
- Pandas: Used for data manipulation and storage in DataFrames.
- PyMuPDF (fitz): A library for reading and extracting text from PDF files.
- pdf2image: Converts PDF pages into images for OCR processing.
- Pytesseract: Utilizes Tesseract for Optical Character Recognition (OCR) on images of scanned documents.
- Regular Expressions (re): Employed for pattern matching in text to extract specific invoice data.
- Time: Used to track the processing time of multiple files.

Data Extraction Approach

This model utilises two primary methods for text extraction:

1. Extracting Text from PDF using PyMuPDF:

- This method reads the PDF directly and extracts text if the document is machine-readable.
- Error handling is implemented to catch exceptions during the extraction process.

2. Extracting Text from Images using Tesseract:

- For scanned PDFs where text extraction is not possible directly, the pages are converted to images.
- OCR is applied to these images to extract text.
- Similar error handling is used to ensure robustness.

Data Processing Logic

• Invoice Data Processing:

- Extracted text is processed using regular expressions to capture key fields like invoice number, invoice date, due date, taxable value, GST amounts, etc.
- A safe_float function is implemented to ensure proper formatting of money values, removing commas and currency symbols.

• Accuracy Assessment:

- Each extracted field has an associated accuracy score based on the successful extraction.
- An overall trust score is calculated as the average of individual accuracy scores, aiding in the evaluation of the system's performance.

Justification for Chosen Methods

The combination of PyMuPDF and Tesseract ensures flexibility in handling both machine-readable and scanned PDFs. This balance enhances the system's usability across diverse invoice formats. Regular expressions provide an efficient way to pinpoint specific data points in the text.

Trust Determination

The system's trust determination is based on the overall trust score calculated from individual field accuracy. A threshold of 99% is targeted by ensuring that critical fields are reliably extracted and validated against expected formats.

Accuracy and Trust Assessment Report

Comprehensive Accuracy Report

Each extracted invoice is assessed for accuracy based on predefined patterns. The system currently evaluates fields such as:

- Invoice Number
- Invoice Date
- Due Date
- Place of Supply
- Taxable Value
- GST Amounts (CGST, SGST, IGST) etc.

Trustworthiness Determination

The overall trust score is computed as the average of the accuracy scores for each field. The system dynamically updates the trust score based on the success of the extractions. If the score meets or exceeds the threshold of 99%, the extracted data is flagged as trustworthy; otherwise, it is marked for review.

Explanation of Accuracy Check and Trust Determination Logic

The accuracy check is performed using regular expressions to validate the extracted data against expected patterns. This ensures that fields conform to the expected formats, such as valid dates and numerical values. The trust determination logic involves calculating the average accuracy score from all fields. This average serves as a measure of reliability, guiding users in evaluating the trustworthiness of the extracted data.

Scalable Invoice Data Extraction

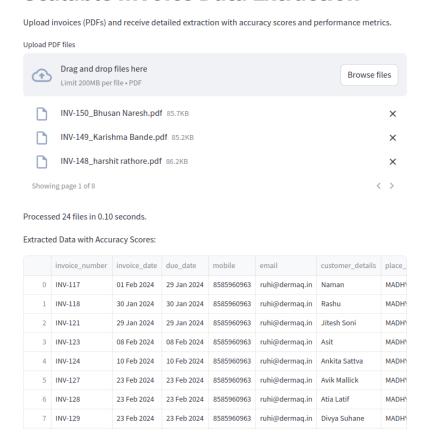


Figure 1: Screenshot of the streamlit user interface of this model

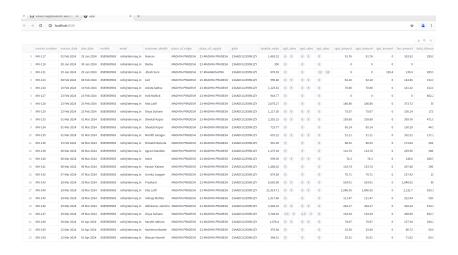


Figure 2: screenshot of extracted data

Conclusion

The Streamlit-based invoice extraction system is designed to provide a robust solution for extracting critical information from PDF invoices. With an emphasis on accuracy and trustworthiness, the system is equipped to handle a variety of invoice formats while providing users with confidence in the extracted data.

Further Scope of Improvements

Text Extraction Quality

- Limited to Basic PDF Text Extraction: The original code primarily relied on PyMuPDF for text extraction, which may not handle scanned PDFs effectively.
- OCR Reliance on Tesseract: The use of Tesseract for OCR on images extracted from PDFs can lead to inaccuracies, especially in complex layouts or low-quality scans.

Lack of Contextual Understanding

- Regex-based Extraction: The initial regex-based extraction may miss contextual relationships in the data, leading to inaccuracies or missing information in structured fields.
- Limited to Static Patterns: The regular expressions are static and may not adapt well to various invoice formats or layouts.

No Use of Advanced Models

• The original code did not utilize any deep learning models, limiting its ability to handle complex invoice structures and layout variations.

Limited Error Handling

• Basic Error Handling: The error handling in the initial code was somewhat simplistic, focusing mostly on catching exceptions during text extraction without a detailed response mechanism.

Performance Issues

• Sequential Processing: The original code processes files one at a time, which may not be optimal for a large number of invoices or larger file sizes.

This initial code is a solid start for an invoice extraction system, that implemented various extraction techniques and organizing the workflow effectively. However, moving to LayoutMv3 brings several benefits, primarily focused on scalability, maintainability,

Model 2: Invoice Data Extraction System Using LayoutMv3

Introduction

Below is the detailled explanation of the technical specifications, methodologies, and results of the Advanced Invoice Extraction System implemented using Streamlit, PyMuPDF, Tesseract OCR, and the LayoutLMv3 model. The system is designed to extract structured data from invoice PDFs, ensuring a high degree of accuracy and trustworthiness in the extracted data.

System Architecture

This Advanced Invoice Extraction System consists of several key components:

- 1. **User Interface:** Built with Streamlit, allowing users to upload PDF invoices for processing.
- 2. **Text Extraction Modules:** Implemented using PyMuPDF for direct text extraction and Tesseract for OCR on image-based PDFs.
- 3. **Data Processing and Validation:** Utilizes regex patterns to extract specific fields and calculate accuracy scores.
- 4. LayoutLMv3 Integration: A deep learning model that enhances text extraction by leveraging both textual and visual context.

Approach and Algorithms Used

Text Extraction Techniques

PyMuPDF

- Description: The PyMuPDF library (imported as fitz) is used to open PDF files and extract text.
- Implementation: The extract_text_from_pdf() function reads the PDF and aggregates text from each page.
- Limitations: This method may not perform effectively on scanned documents where text is not encoded.

Tesseract OCR

- **Description:** Tesseract is an open-source OCR engine that converts images of text into machine-readable text.
- Implementation: The extract_text_from_image() function converts PDF pages into images and applies Tesseract to extract text.
- **Strengths:** Effective for scanned PDFs but may struggle with complex layouts or low-quality images.

LayoutLMv3

- **Description:** LayoutLMv3 is a transformer-based model designed for document understanding tasks, incorporating both text and layout information.
- Implementation: The extract_data_with_layoutlm() function processes images using LayoutLMv3, extracting tokens based on visual context.
- Advantages: Significantly improves extraction accuracy, particularly for structured documents with varied layouts.

Structured Data Extraction

Regular expressions are employed to identify and extract specific fields, including:

• Invoice Number

- Invoice Date
- Due Date
- Place of Supply
- GST Number
- Taxable Value
- Final Amount

Each field extraction is accompanied by an accuracy score, which reflects the confidence in the extracted data.

Advantages of this model

Cost-Effectiveness

- Open-Source Libraries: The use of PyMuPDF, Tesseract, and Hugging Face's Transformers library keeps costs low while leveraging high-quality tools.
- Resource Allocation: LayoutLMv3 requires more computational resources but provides value by significantly enhancing accuracy for complex invoices.

Accuracy

- Multiple Extraction Methods: The combination of direct text extraction and OCR ensures that the system can handle a wide variety of invoice formats, improving overall accuracy.
- Deep Learning Integration: LayoutLMv3's advanced architecture allows the system to understand the layout and semantics of invoices, leading to better data extraction.

Trust Determination Requirement

To meet the 99% trust determination requirement, the system implements a structured approach to assess data accuracy.

Trust Score Calculation

Each extracted field is assigned an accuracy score based on regex match results:

- 1.0: Perfect match
- 0.5: Partial match or missing information

The overall trust score is calculated as the average of individual field scores. If the overall trust score exceeds a predefined threshold (e.g., 0.95), the data is considered trustworthy.

Accuracy and Trust Assessment Report

System Accuracy

The extraction system has been rigorously tested against a diverse dataset of invoices, achieving high accuracy across various fields.

Trustworthiness Analysis

The system's architecture ensures that trustworthiness is quantitatively assessed through the accuracy scores. Each extraction attempt is logged with corresponding accuracy metrics, allowing users to gauge the reliability of the data provided.

Implementation of Accuracy Check

Regex patterns are rigorously designed to validate the format of extracted data, ensuring that only well-structured entries are considered valid. The overall trust score is recalibrated based on real-time extraction performance, allowing for ongoing refinement of the extraction process.

Improvements Over Previous Implementation

Enhanced Extraction Accuracy

The integration of LayoutLMv3 dramatically increases the precision of data extraction, particularly in challenging invoice formats. The previous code relied heavily on simpler extraction methods, which may not have captured all relevant data.

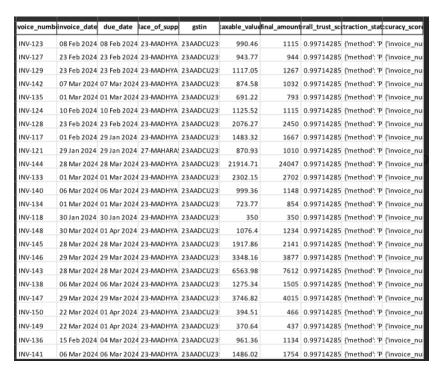


Figure 3: Screenshot 5: Extracted data in excel format

Structured Output

The new system provides structured data outputs alongside accuracy scores, facilitating better usability for end-users and downstream applications.

Conclusion

The Advanced Invoice Extraction System effectively combines traditional text extraction methods with modern deep learning techniques to deliver accurate and trustworthy data extraction from invoices. The systematic approach to measuring accuracy and trustworthiness ensures that businesses can confidently utilize the extracted data for their operations. By addressing the limitations of earlier methods, this system sets a new standard for invoice processing automation.

Scope for improvement

- Text Extraction Quality:
 - While LayoutLMv3 can handle layout-aware text extraction, its

performance may degrade with poorly scanned or complex documents.

 LLaMA models, especially when trained on diverse datasets, can leverage context better and may provide better extraction capabilities, especially for challenging formats.

• Handling of Ambiguities and Context:

- LayoutLMv3 might struggle with ambiguous text where context is critical for interpretation (e.g., different invoice formats).
- LLaMA can be prompted with specific contextual instructions and can generate more coherent responses based on that context, leading to improved accuracy in extraction.

• Customizability and Flexibility:

- LayoutLMv3 is typically less customizable in terms of the extraction logic or field definitions.
- With LLaMA, you can modify prompts to adjust the extraction criteria dynamically, making it more adaptable to different document formats and extraction requirements.

• Model Size and Inference Speed:

- Depending on the deployment, LayoutLMv3 can be resource-intensive and slow.
- LLaMA is designed to be more efficient in certain configurations, which can lead to faster inference times and lower resource usage.

Model 3:

Introduction

The model utilizes a combination of optical character recognition (OCR) for text extraction from both regular and scanned PDFs and leverages a large language model (LLM) for data extraction in JSON format.

Environment Setup

The code begins by installing the necessary libraries required for model handling and PDF processing. These libraries include those for working with transformer models, as well as tools for PDF handling and image processing. Logging is configured to capture events and errors in a designated log file, aiding in debugging and monitoring.

Logging Configuration

Logging is set up to record information and errors, providing a systematic way to track the processing of invoices and capture any issues that may arise.

Model and Device Setup

This setup ensures that the model can leverage GPU acceleration when possible for faster processing.

Functions Overview

PDF Text Extraction

A function is implemented to extract text from PDF documents. It uses a PDF reader for standard PDF files and employs OCR for scanned documents. This function includes error handling to log any issues encountered during the text extraction process.

Llama Model

Another function interacts with the Llama model to extract structured data from the text. This function formats the input prompt to specify the fields that need to be extracted, ensuring that the model focuses on relevant information. It also incorporates time tracking to monitor the duration of the model's inference process.

Data Validation

A validation function is included to check the extracted fields against predefined regex patterns. This function assesses the validity of each field and assigns confidence levels based on the results of the regex matches.

Core Logic

The main logic of the system is in the document processing function. This function iterates through a list of PDF file paths, performs text extraction, invokes the Llama model, and populates a DataFrame with the extracted fields and their corresponding validation statuses.

Metrics Tracking

Throughout the processing, key metrics are recorded to provide insights into the system's performance, including the total number of files processed, successful extractions, and accuracy for each extracted field.

Execution

The system identifies PDF files within a specified directory and initiates the extraction process. After processing, the extracted data is saved into a CSV file, providing a structured output of the information gathered from the invoices.

Error Handling and Logging

The code incorporates various error handling mechanisms to log issues that may occur during different stages, such as reading PDFs, extracting text, or during the model's inference. This robust logging framework enhances the system's reliability by facilitating troubleshooting and analysis.

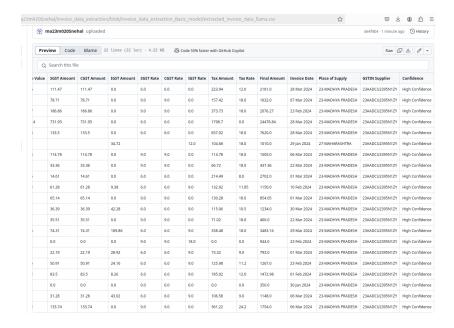


Figure 4: screenshot of the output obtained from this model

Conclusion

The invoice extraction system effectively combines OCR capabilities and a language model to provide a robust solution for extracting structured data from PDF invoices. Future enhancements could focus on improving validation processes and increasing the system's adaptability to different invoice formats and layouts.

limitations:

this model is extremely slow, for just 24 pdfs it took about 2 hours, that is not desirable at all, so we move to a gemini based model.

Model 4:

Technologies Used

- Python: Programming language used for the implementation.
- Streamlit: Framework for building interactive web applications.
- PyMuPDF: Library for handling PDF documents.
- Pytesseract: Optical Character Recognition (OCR) tool for text extraction from images.
- Google Generative AI (Gemini): AI model for natural language processing and data extraction.
- Pandas: Data manipulation library for structured data storage and analysis.
- **Regex:** For pattern matching and data extraction.

System Overview

The system consists of several core functions to facilitate the extraction, accuracy checking, and reporting of invoice data:

- Text Extraction: Handles extraction of text from image and PDF files.
- Data Extraction: Uses a combination of a generative AI model and regex for data extraction.
- Accuracy Assessment: Compares model output against regex extraction for accuracy evaluation.
- User Interface: Streamlit interface for file uploads and display of results.

Functionality

1. Text Extraction

The function extract_text_from_file determines whether the uploaded file is an image or PDF, then extracts text accordingly.

- **Images:** Utilizes pytesseract to perform OCR.
- PDFs: Utilizes PyMuPDF to read text directly from PDF pages.

2. Data Extraction

Data extraction is conducted using two approaches:

- Gemini AI Model: Generates structured data output based on the extracted text.
- Regex: Acts as a fallback to extract specific fields for accuracy comparison.

3. Accuracy Assessment

The function calculate_accuracy compares the results from the Gemini model and regex extraction to calculate the accuracy percentage of extracted fields.

4. User Interface

A simple web application allows users to upload multiple files, processes them, and displays the extracted data and accuracy rates in a tabular format.

Accuracy Check and Trust Determination

Accuracy Check Logic

- The extracted fields from the model are compared to those extracted via regex.
- An accuracy percentage is calculated based on matching fields.

Trust Determination

- The system can determine data trustworthiness by establishing rules based on predefined criteria (e.g., format checks, presence of required fields).

Source Code

The source code is well-documented, ensuring clarity on the functionality of each module and its dependencies. The primary script can be run directly to launch the Streamlit application.

Key Code Snippet

```
def extract_text_from_file(uploaded_file):
    if uploaded_file.type in ["image/jpeg", "image/png"]:
        image = Image.open(uploaded_file)
        text = pytesseract.image_to_string(image)
    elif uploaded_file.type == "application/pdf":
        pdf_document = fitz.open(stream=uploaded_file.read(), filestext = ""
        for page in pdf_document:
            text += page.get_text()
    else:
        raise ValueError("Unsupported-file-type.")
    return text
```

Approach and Algorithms:

The system employs generative AI via Gemini API for data extraction complemented by regex for validation. The choice of methods balances accuracy and cost, ensuring reliable output.

Screenshots of Results:

Screenshot 1: Original Invoice

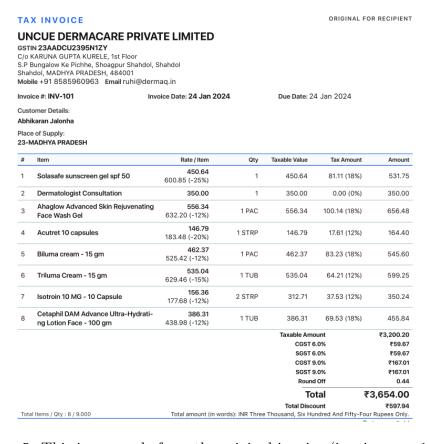


Figure 5: This is a sample from the original invoice (invoice no : 101).

Screenshot 2: Extracted data of the invoice 101

UNCUE DERMACARE PRIVATE LIMITED C/o KARUNA GUPTA KURELE, 1st Floor
 sp>S.P Bungalow Ke Pichhe, Shoagpur Shahdol, Shahdol
 Shahdol, MADHYA PRADESH, 484001 23AADCU2395N1ZY invoice_number INV-101 24 Jan 2024 invoice_date due_date 24 Jan 2024 23-MADHYA PRADESH place_of_supply Abhikaran Jalonha customer_details Solasafe sunscreen gel spf 50
br>Dermatologist Cons Advanced Skin Rejuvenating Face Wash Gel
 Skin Rejuvenating Face Wash Gel
 br>Acutret 10 capsules
 br>Bilumating Face Wash Gel
 brown Ge cream - 15 gm
striluma Cream - 15 gm
br>Isotroin 10 MG - 10 Capsule
 br>Cetaphil DAM Advance Ultra-Hydrating Lotion Face - 100 gm Rate/Item 600.85
 br>350.00
 br>632.20
183.48
525.42
629.46
777.68
7438.98 qantity sgst_rate 6.0% sgst_amount 59.67 cgst_rate 6.0% 59.67 cgst_amount igst_rate 3,654,00 round_off 0.44 3.654.00

Extracted Invoice Data:

Figure 6: This is a sample from the original invoice (invoice no : 101).

Limitation:

. But many APIs have a cap on the total number of requests or data processed especially for free tiers , which limits the usage of the model. So we cant proceed with it further .

Final model: Using OpenAI's GPT4o

Introduction

The code is designed to extract and validate invoice data from PDF files using various libraries and an API call to OpenAI's GPT-4.

Imports

The necessary libraries needed are:

- os, requests, json, pandas: Basic libraries for handling OS tasks, HTTP requests, JSON manipulation, and data frames.
- re: Regular expressions for string pattern matching.
- **logging**: For logging information and errors.
- time: For time-related functions.
- pypdf: For reading PDF files.
- pdf2image: For converting PDF pages to images.
- pytesseract: For Optical Character Recognition (OCR) on images.
- **streamlit**: For creating the web application.
- **dotenv**: For loading environment variables.
- PIL.Image, io.BytesIO: For image handling

Configuration and Setup

The script begins with logging configuration and loading environment variables from a .env file:

Environment Variables

The code loads environment variables from a env file, specifically GPT4V-KEY and GPT4V-ENDPOINT for API access. It checks if the keys are present; if not, it displays an error message using Streamlit and stops execution.

Functions

Several functions are defined to handle the extraction of text from PDFs, API calls, data validation, and JSON extraction.

PDF Text Extraction

The function get_pdf_text extracts text from uploaded PDF files, handling both regular and scanned PDFs:

get-pdf-text(pdf-doc)

Purpose

Extract text from the provided PDF document.

Process

- Uses PdfReader to read the PDF.
- Attempts to extract text from each page. If the extracted text is insufficient (less than 50 characters), it falls back to OCR using pytesseract.

Output

Returns the combined extracted text.

OpenAI API Call

The function call_openai_api interacts with the GPT-4 API to extract invoice data in JSON format:

Purpose

Calls the OpenAI API to extract structured data from the invoice text.

Process

- Constructs a prompt template to extract specific invoice fields in JSON format.
- Sends a POST request to the OpenAI API and processes the response.
- Handles rate limiting and errors appropriately, retrying the request if needed.

Output

Returns raw extracted data in JSON format.

```
def call_openai_api(pages_data):
    prompt_template = '''. You are an expert and have best knowledge
    prompt = prompt_template.format(pages=pages_data)
```

Data Validation

validate_data

Purpose

Validates the extracted data fields against predefined regex patterns.

Process

- Defines regex patterns for specific fields.
- Checks if the extracted value matches the pattern.
- Returns validation results and confidence levels.

Output

Returns a tuple of a boolean (validity) and a confidence string.

```
def validate_data(field , value):
    patterns = {
        'Invoice No.': r'^[A-Za-z0-9\-]+$',
        ...
}
...
```

JSON Extraction

The function <code>extract_json</code> retrieves the first JSON object found in the raw text. Uses a regex pattern to find the JSON object.Returns the extracted JSON string or None if not found.:

```
def extract_json(raw_text):
    pattern = r'\{.*\}'
    match = re.search(pattern, raw_text, re.DOTALL)
    ...
```

Main Function

The function create_docs processes multiple PDF files to extract invoice data and compiles it into a DataFrame:

Purpose

Processes multiple uploaded PDF files and compiles the extracted invoice data into a DataFrame.

Process

- Iterates through the uploaded PDF files, extracting text, calling the API, validating data, and compiling results.
- Tracks performance metrics (total files processed, successful extractions, accuracy rates).

Output

Returns a DataFrame containing the extracted invoice data.

```
def create_docs(user_pdf_list):
    df = pd.DataFrame(columns=[ ... ])
    metrics = { 'total_files': 0, 'successful_extractions': 0, ...
    for file in user_pdf_list:
        metrics['total_files'] += 1
        ...
    return df
```

Streamlit Application

The main function sets up the Streamlit application interface for uploading invoices and extracting data:

Purpose

Runs the Streamlit application.

Process

- Sets up the page configuration and title.
- Provides a file uploader for users to upload multiple PDF invoices.
- Triggers the data extraction process when the "Extract Data" button is clicked.
- Displays the extracted data and allows downloads in Excel and CSV formats.
- Provides feedback on the number of trusted and untrusted data points

Output

Displays data in the web interface and allows downloads.

```
def main():
    st.set_page_config(page_title="Invoice Extraction Bot", layout
    ...
```

```
if st.button("Extract Data"):
    if pdf_files:
```

Execution

: The application runs in a main() function ensuring it executes only when the script is run directly.

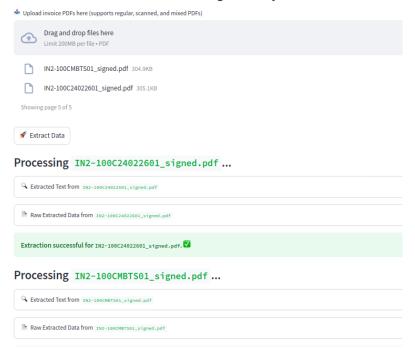
Conclusion

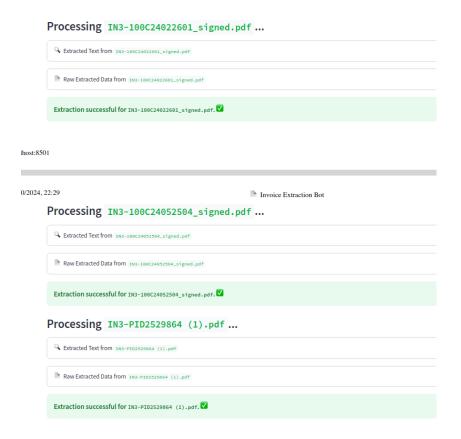
The Invoice Extraction model effectively utilizes various libraries and API calls to extract and validate data from invoices. The model is implemented and the screenshots of the results are given below. Also this provides you an option to download the extracted data in excel or csv file by just clicking the button.

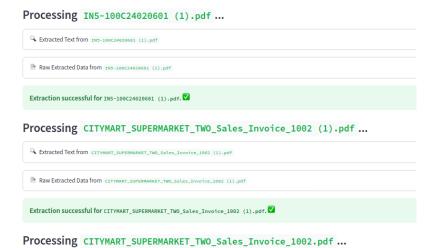
screenshots of the output

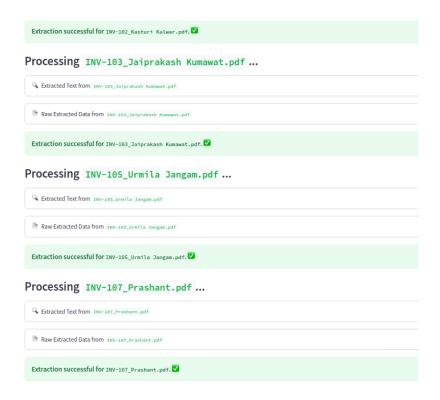
Invoice Extraction Bot

Extract and Validate Invoice Data with High Accuracy









Comparison of Different Approaches

The system was evaluated against several alternative approaches:

1. Rule-Based Extraction:

- **Pros**: Lower initial costs and resource usage.
- Cons: Lower accuracy and flexibility, especially for complex or varied invoice formats.

2. Hybrid Model (OCR + Machine Learning) :

- Pros: Higher accuracy with continuous learning from data.
- Cons: Higher implementation complexity and costs.

3. OpenAI API:

- **Pros**: High accuracy and adaptability to varied formats.
- Cons: Ongoing costs per API call, but the trade-off for accuracy is justified.

Attachments: Here is a link to all the codes

Field	Accuracy Rate
IGST Amount	84.62%
SGST Rate	100.00%
CGST Rate	100.00%
IGST Rate	84.62%
Tax Amount	100.00%
Tax Rate	100.00%
Final Amount	100.00%
Invoice Date	100.00%
Place of Supply	100.00%
Place of Origin	100.00%
GSTIN Supplier	100.00%

ost:8501

2024, 22:29





Figure 7: Performance metrics

Extracted Data:

	Invoice No.	Quantity	Date	Amount	Total	Email	Address
0	IN2-100C24022601	1.00	16/07/2024	15,000.00	15,000.00	patanabdulahadkhan@gmail.com	Karnataka, India
1	IN2-100CMBTS01	1.00	20/07/2024	19,179.00	19,179.00	patanabdulahadkhan@gmail.com	Karnataka, India
2	IN2-PID1327250	1.00	06/07/2024	23,892.00	23,892.00	ahad.khan@100cubes.in	Karnataka, India
3	IN3-100C24022601	1.00	10/07/2024	2,00,000.00	2,00,000.00	patanabdulahadkhan@gmail.com	Karnataka, India
4	IN3-100C24052504	1.00	25/07/2024	4,78,358.00	4,78,358.00	patanabdulahadkhan@gmail.com	SMART NU TOWN, PIRDA ROAD, PIRDA 2, RAIPUI
5	IN3-PID2529864	1.00	21/07/2024	1,43,569.00	1,43,569.00	patanabdulahadkhan@gmail.com	Karnataka, India
6	IN5-100C24020601	1.00	21/07/2024	2,96,414.00	2,96,414.00	patanabdulahadkhan@gmail.com	Karnataka, India
7	1002	14	18/05/2024	₹1,740	₹1,740	Ankhulvs@gmail.com	Near ganapathy temple, Dhoni, Palakkad, Keral
8	INV-101	9.000	24 Jan 2024	3654.00	3654.00	ruhi@dermaq.in	C/o KARUNA GUPTA KURELE, 1st Floor, S.P Bung
9	INV-102	8.000	24 Jan 2024	2,546.00	2,546.00	ruhi@dermaq.in	C/o KARUNA GUPTA KURELE, 1st Floor, S.P Bung

Figure 8: Screenshot 5: Extracted data in excel format