INTERNSHIP PROJECT REPORT

ON

“Handwritten Text OCR and Storage”

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Internship Duration: 5th May to 1st July 2025

Date**:** 1st July 2025

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CERTIFICATE

This is to certify that **Mr. Anant Arora**, a student of B.Tech in Data Science, has successfully completed his **internship** work.

During this period, he worked diligently on a project titled:
“Handwritten Table Recognition ”, under the expert guidance and mentorship of the Digital Department at Aurobindo Pharma.

As part of this project, he developed a complete end-to-end pipeline using state-of-the-art Optical Character Recognition (OCR) techniques. The system accurately extracts handwritten tabular data and stores it systematically in an SQL Server database. He also implemented a user-friendly frontend using Streamlit for seamless data interaction.

He has demonstrated commendable technical skills, problem-solving ability, and commitment throughout the internship. He has successfully built and deployed a working model for handwriting OCR and data storage under professional constraints.

We appreciate his contribution and wish him continued success in his future endeavours.

Mr Mohan Krishna Kokkiligadda
(Project Guide / Mentor)
Aurobindo Pharma Ltd

Date: 1st July 2025

Acknowledgment

I take this opportunity to sincerely thank everyone who supported me throughout the duration of this project. Their contributions, guidance, and encouragement have been invaluable to the successful completion of this work.

First and foremost, I would like to express my deep sense of gratitude to my senior, **[Senior's Full Name]**, for their consistent guidance, technical mentorship, and constructive feedback at every stage of the project. Their insights not only helped me overcome technical hurdles but also shaped my problem-solving approach, which was critical to the development of the system.

I extend my sincere thanks to **Eugia Pharma** for selecting me to work on this project. I am truly honored to have had the opportunity to contribute to an industry-level use case that aims to solve a relevant problem in document automation and data extraction. The resources, domain knowledge, and trust extended to me by Eugia Pharma created an excellent environment for both learning and innovation.

This project, which focused on building an OCR-based data extraction system for handwritten and typed medical tables, served as a transformative learning experience. It offered me an opportunity to apply theoretical concepts in real-world scenarios, refine my technical skills in Python, OCR libraries, and SQL databases, and understand the practical challenges in handling noisy, unstructured data

In conclusion, I would like to thank everyone who played a role, directly or indirectly, in the success of this project. This experience has not only strengthened my technical foundation but also helped me grow professionally and personally. I look forward to carrying forward these learnings into future projects and challenges.

Abstract

This project focuses on the development of a complete Optical Character Recognition (OCR) system designed to extract tabular data from both typed and handwritten documents and systematically store the information in a secure SQL Server database. The solution was developed with a strong emphasis on real-world applicability, especially in enterprise contexts such as pharmaceutical data management.

The system integrates multiple OCR models, including **EasyOCR**, **PaddleOCR**, and **Tesseract**, and employs a combination of **preprocessing**, **box detection**, and **post-processing** to accurately parse and interpret tabular structures. A custom Python-based backend handles data cleaning and parsing, while a **Streamlit-based frontend** allows for real-time interaction and visualization. For typed documents, the system achieves a high accuracy of over 95%. However, handwritten data posed challenges due to the absence of a dedicated dataset and computational limitations for model fine-tuning.

Despite these challenges, the project successfully establishes a modular and extensible OCR-to-database pipeline that can be further enhanced using GPU acceleration and domain-specific data. The end result is a practical and scalable tool for document digitization, enabling automated extraction, classification, and storage of critical material information.

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Chapter 1: Introduction

1.1 Problem Statement – The Need for a Handwriting Recognition Model in Pharmaceutical Documentation:

In today's fast-paced and documentation-heavy industries like pharmaceuticals, a significant portion of operational and clinical records are still maintained manually, often through handwritten entries. This is especially common in-patient forms, inventory records, internal communication, prescription documentation, and quality assurance logs. Despite advancements in digital technologies, handwritten documentation remains a critical part of everyday workflows in pharmaceutical settings due to regulatory practices, legacy systems, and on-the-ground constraints.

However, one of the major challenges with handwritten data is its **inconsistency**. Every individual has a unique handwriting style, and when information is written quickly — as is often the case in high-pressure environments like hospitals or production floors — the legibility of that handwriting tends to deteriorate. Characters may become distorted, overlapping, or unclear, making it difficult for others to interpret the information accurately.

This becomes particularly problematic when sensitive data such as medicine names, chemical codes, batch numbers, or dosage instructions are involved. A misread code or an incorrectly interpreted drug name can have serious consequences. These include:

- Dispensing the wrong medication or dosage,
- Delays in patient treatment,
- Errors in production or inventory,
- Regulatory compliance failures,
- And ultimately, significant financial and reputational damage to the company.

Such risks make it imperative to adopt solutions that minimize human error in interpreting handwritten content. A robust **Handwriting Recognition Model**, specifically tailored for structured data such as tables, can play a crucial role in addressing these challenges. It enables:

- Automated extraction and digitization of handwritten tables,
- Accurate mapping of values such as codes, quantities, and labels,
- Seamless integration into backend databases (e.g., SQL),
- Reduction in manual data entry, and

- Lower operational overhead due to reduced human intervention.

By implementing such a model, pharmaceutical companies like Eugia can not only enhance the accuracy and reliability of their documentation processes but also **increase overall operational efficiency**, improve regulatory compliance, and ensure safer handling of critical data.

In summary, a handwriting recognition model is not just a technical enhancement but a strategic necessity for pharmaceutical companies aiming to modernize their workflows, mitigate risk, and ensure precision in every written word that flows through their systems.

1.2 Importance in Pharma – Role of Handwritten Documentation in Medicine Manufacturing

In a large pharmaceutical organization like Eugia Pharma, the manufacturing process is governed not only by precise formulations but also by rigorous documentation standards. Every batch of medicine produced is meticulously logged — from raw material intake to final packaging. These logs often contain critical information such as material codes, medicine names, batch numbers, dates, quantities, and operator initials. In many cases, especially on manufacturing floors and quality control labs, these records are still maintained by hand due to on-ground feasibility, regulatory requirements, or lack of digital infrastructure at specific checkpoints.

Handwritten entries form the foundation for inventory reconciliation, traceability, audit trails, and USFDA compliance. The material code in these logs is especially crucial — it acts as a unique identifier for each drug component and helps verify the identity, composition, and authenticity of every medicine batch. Even a minor error in interpreting this information can disrupt the traceability chain, cause production delays, or even trigger compliance violations.

For instance, if the handwritten material code is misread or entered incorrectly, it could lead to:

- Usage of the wrong compound during mixing,
- Mismatch between documentation and actual inventory,
- Errors in labelling and packaging,
- Risk of regulatory action during audits.

Given that the **USFDA and other global regulatory bodies** closely inspect such records during compliance audits, maintaining accurate, legible, and traceable documentation is not optional — it is critical.

This is precisely where a **Handwriting Recognition Model** becomes a game-changer. By converting handwritten entries from logs into structured digital formats like spreadsheets or SQL tables, this model offers several key advantages:

- Reduces human error in reading or transcribing handwritten content.
- Ensures consistency and traceability of material codes and medicine names.
- Automates the transfer of handwritten logs into digital systems.
- Facilitates real-time data access and integration with existing ERP or inventory systems.
- Improves audit readiness and reduces compliance risk.

By implementing this model across its manufacturing and documentation workflow, Eugia can significantly improve data integrity, **streamline manual processes**, and enhance overall operational efficiency. In a domain where even a single misread digit can cost lakhs — both financially and reputationally — this solution isn't just an innovation; it is a **strategic safeguard**.

1.3 Challenges with Handwriting in Structured Data (Tables)

Unlike printed text, handwritten data is inherently inconsistent. Every individual has a unique style of writing — shaped by their education, native language, speed of writing, and even their mood at the moment. This variability poses serious challenges when the goal is to accurately interpret handwritten information, especially within **structured formats such as tables**, where precision in position and value is critical.

In a pharmaceutical context, where tabular logs are used to record medicine names, material codes, batch numbers, and quantities, even a small handwriting inconsistency can lead to incorrect interpretation. Some of the common challenges observed include:

- **Varying character shapes**: The same letter can appear drastically different across individuals. For instance, the letter **"g"** or **"r"** can be printed in multiple styles or written in cursive, often making it difficult for OCR models to generalize.
- **Cursive or connected writing**: Many individuals use cursive writing, where letters flow into each other. This makes it hard for character-level OCR models to distinguish where one letter ends and the next begins — especially in tight spaces like table cells.
- **Writing outside cell boundaries**: Structured forms rely on users to write within the confines of rows and columns. In practice, handwritten entries often **spill over** these boundaries — either vertically or horizontally — disrupting the logical mapping between data values and their corresponding fields.

- **Non-linear writing**: Some people don't write in a straight line, especially when no guiding rule lines are present. Words may slope upwards or downwards within the same cell, making segmentation and recognition more complicated.
- **Irregular spacing**: In printed documents, spaces clearly separate words or numbers. In handwriting, spacing is subjective. A person might leave a large gap between letters of the same word or cramp two words together, making it difficult for the system to accurately tokenize the content.
- **Noise from overlapping strokes and table lines**: Characters often interfere with grid lines in the table, especially in scanned copies. This adds **visual noise** that must be filtered out during preprocessing, increasing the complexity of the task.
- **Speed-induced degradation**: When individuals write quickly — which is common on manufacturing floors or during busy shifts — legibility is further compromised. Letters may be skipped, strokes may be incomplete, and numbers may resemble each other.

These inconsistencies collectively make it extremely difficult for standard OCR systems to extract meaningful data from structured handwritten formats. Unlike typed documents, where data extraction is largely deterministic, handwritten tables require intelligent models that can account for human variability in writing. This reinforces the need for a specialised handwriting recognition pipeline that includes preprocessing, structure detection, and robust model architectures capable of handling real-world handwriting diversity.

1.4 Objectives of the Project

The primary objective of this project is to design and implement a complete, end-to-end handwriting recognition pipeline tailored for pharmaceutical documentation — particularly handwritten tables found in material logs, manufacturing records, and inventory sheets. Unlike general-purpose OCR tools, this system is customized to handle the inconsistencies and complexities of real-world handwritten entries, transforming them into structured, digital SQL records for downstream use.

The model was developed with the goal of making the digitisation of handwritten documentation seamless, accurate, and scalable. Given that pharmaceutical manufacturing involves strict compliance, material tracking, and audit readiness, it is essential that handwritten data — especially tables — be interpreted correctly and stored in a usable format. This system addresses that requirement by providing a robust solution that functions across different handwriting styles and varying quality of scanned documents.

The pipeline is structured into the following core stages:

1. **Image Preprocessing**: The raw input — typically scanned copies of handwritten logs — is cleaned using a combination of OpenCV techniques. This includes grayscale conversion, noise reduction, thresholding, and table boundary detection. This stage ensures that the input is optimized for accurate character recognition.
2. **Model Inference**: Once pre-processed, the image is passed through a selected OCR engine. Multiple models were explored during development, including Tesseract, EasyOCR, PaddleOCR, and a custom CNN + CTC architecture trained on a proprietary handwriting dataset. Each model's performance was benchmarked to identify strengths under different writing styles and conditions.
3. **Postprocessing and Table Structuring**: After raw text is extracted, the data is cleaned, parsed, and formatted to align with a tabular schema. Custom logic ensures that each recognised value is placed in the correct row and column, preserving the original structure and meaning of the handwritten input.
4. **SQL Storage and Integration**: The final structured data is inserted into an SQL database (e.g., MySQL or PostgreSQL), where it can be queried, audited, or visualised. This creates a permanent digital record of what was once manually written, enabling integration with inventory systems, compliance logs, or dashboards.

By automating this entire workflow, the model significantly reduces human intervention in the documentation process, minimises errors, and increases traceability — all while improving the organisation’s ability to handle handwritten logs more efficiently. In summary, this project aims not just to recognize handwriting but to transform unstructured human input into structured, actionable data, ready for enterprise-scale use.

Chapter 2: Tech Stack & Tools Used

To build a robust handwriting recognition system capable of extracting structured data from handwritten tables, a variety of programming languages, models, libraries, and frameworks were used. Each component played a specific role in different stages of the pipeline — from data preprocessing to model inference and final SQL storage. Below is the categorized breakdown of all technologies utilized in the project:

Programming Language

Python

Python served as the core programming language for the entire project due to its extensive support in the machine learning, image processing, and data engineering ecosystems. It enabled quick prototyping, integration of OCR models, and handling of file I/O, database connectivity, and visualization tasks.

OCR Models & Architectures

Tesseract OCR

An open-source OCR engine developed by Google, used for baseline experimentation. It supports different page segmentation modes (PSM) and language models. Tesseract performed reasonably well on clean prints but struggled with cursive and inconsistent handwriting.

EasyOCR

EasyOCR is a lightweight deep learning-based OCR library that works well with multiple languages. It was tested for its ability to read connected cursive handwriting, offering decent performance in low-noise environments but less reliable in structured table formats.

PaddleOCR

Built on top of PaddlePaddle, PaddleOCR supports layout analysis and multi-stage text detection. Its ability to extract text from complex layouts made it a good candidate for structured forms and tables. It was especially effective in recognizing text blocks across varying styles.

Custom CNN + CTC Architecture

A custom deep learning model was built using convolutional neural networks for feature extraction and a CTC (Connectionist Temporal Classification) layer for decoding sequence-based outputs. This model was trained on a proprietary handwriting dataset and optimized for structured handwritten text, outperforming pre-trained OCRs in accuracy and flexibility.

Libraries & Tools

OpenCV

Used extensively in the preprocessing stage for tasks like grayscale conversion, noise filtering, thresholding, contour detection, and line removal. OpenCV played a crucial role in cleaning and isolating content from scanned handwritten forms.

Pandas

Pandas was used to structure and manipulate data extracted from the OCR pipeline. It helped in aligning recognized content into tabular form before sending it for SQL insertion.

SQL (MySQL/PostgreSQL)

Structured output from the pipeline was inserted into SQL databases to enable querying, storage, and downstream use. Both MySQL and PostgreSQL were considered, with SQL schemas designed to mimic the original data logs for traceability and audit readiness.

Modules & Encoding Techniques

Label Encoding + Custom Dataset

Since no public dataset suited the pharma domain's needs, a custom dataset was manually created and label-encoded for training the CNN+CTC model. Characters were mapped to numeric values for compatibility with the model's output format, ensuring consistent decoding.

TensorFlow

TensorFlow was used as the underlying deep learning framework for building and training the custom CNN+CTC model. It provided flexibility for defining sequential architectures and optimizing training performance.

Matplotlib

This module was used for visualizing training metrics such as loss curves, accuracy graphs, and confusion matrices. It helped in diagnosing model behavior and validating results over training epochs.

Each of these tools was selected after careful evaluation and contributed to making the overall pipeline **modular, scalable, and production ready**. The integration of multiple OCR methods also enabled benchmarking and comparison across different handwriting styles.

Chapter 3: Dataset Preparation

3.1 Why a Custom Dataset Was Necessary

n pharmaceutical manufacturing environments such as Eugia Pharma, documentation plays a critical role in ensuring compliance, traceability, and operational transparency. However, much of this documentation—ranging from batch records to material usage logs—is handwritten and confidential in nature.

Due to the strict privacy protocols mandated by internal audit policies and external regulatory bodies such as the USFDA, it was not feasible to utilize actual company data for training machine learning models. This includes medicine codes, material identifiers, and production logs, which are considered proprietary and legally protected.

To address this challenge, a synthetic dataset was created that simulated the appearance, structure, and complexity of real handwritten logs. This custom dataset not only adhered to compliance standards but also offered full control over content, which was essential for training and evaluating models effectively.

3.2 Data Generation Strategy Using Python

The synthetic dataset was generated using a custom Python script built on top of libraries such as **Pillow**, **Pandas**, and standard Python modules. The objective was to create tabular images that closely mimic the handwritten entries found in real-world pharmaceutical forms.

Each generated image represents a structured table containing five rows and five columns. The columns typically include:

- Material Code
- Unit of Measurement (UOM)
- Quantity Issued
- Quantity Returned
- Lot Number

To simulate handwriting, two different open-source handwritten fonts were used.

Material Code	UOM	Quantity required	Quantity issued	Lot No.
ANFC6MCM	KG	715	567	WNA271FDTIY
AVHU4FAB	PC	764	17	oIDST2KH8U9M
T2NXGALTL	PC	532	757	M6VGTOPVMFS
STST91XG	ML	355	53	Y274CC9VUHS
AYROOELH	KG	343	163	LS147GU61TN

3.3 Code Logic Behind Image and Label Generation

The core logic of the data generation script revolves around the following sequence:

1. Canvas Creation

A blank canvas was initialized using the Image.new() function from the Pillow library. The canvas had a fixed resolution and a white background, simulating a scanned document.

```
for file_num in range(1, 101):
    font_path = font_files[file_num % len(font_files)]
    font_handwritten = ImageFont.truetype(font_path, 22)

    img = Image.new('RGB', (width, height), color='white')
    draw = ImageDraw.Draw(img)
```

2. Table Structure Drawing

The table's boundaries were created by drawing horizontal and vertical lines at calculated positions based on the width of the image and the number of rows and columns.

```
for i in range(7):
    y_line = table_top + i * row_height
    draw.line([(0, y_line), (width, y_line)], fill='black', width=2)
for x in x_positions + [width]:
    draw.line([(x, table_top), (x, table_top + row_height * 6)], fill='black', width=2)
```

This code block ensures that all cells are uniformly spaced, and the grid closely resembles a hand-drawn table on a printed form.

3. Randomized Row Data Insertion

Each cell in the table was populated with randomly generated values. The generation functions were designed to mimic pharmaceutical data, such as alphanumeric material codes or numerical quantities.

```
for row in range(1, 6):
    y_text = table_top + row * row_height + 15
    row_data = [
        random_material_code(),
        random_uom(),
        random_quantity(),
        random_quantity(),
        random_lot()
    ]
```

Each random_ function returns pseudo-realistic values:

- random_material_code() generates codes like "ALP2042"

- random_uom() randomly selects from units like “MG”, “ML”, “G”
- random_quantity() returns floating point values or integers
- random_lot() generates lot numbers in a standard format like “LOT-1892”

This data was then placed inside the table using the draw.text() method, which applies the selected handwritten font.

```
for i, text in enumerate(row_data):
    draw.text((x_positions[i] + 15, y_text), text, font=font_handwritten, fill='black')
labels_data.append([f"table_{file_num:03d}.png"] + row_data)  # 🔄 Changed extension to .png
```

To increase variability, different fonts were used for each dataset, so that the resulting model could learn to handle different handwriting patterns.

4. Label Creation and Storage

Simultaneously, for every table created, the corresponding labels were stored as a list. Each label includes the filename and the content of each row in order.

```
# Save labels to CSV
df = pd.DataFrame(labels_data, columns=["filename"] + columns)
df.to_csv(os.path.join(output_dir, "labels.csv"), index=False)
```

This ensured that each table image had an exact, structured label counterpart — essential for training OCR models that expect supervised learning formats.

5. File Saving

Each generated image was saved in PNG format for better compatibility with OCR pipelines. In addition, the image was also exported to PDF to simulate a real-world document scan if needed.

```
# Save PDF
img.save(os.path.join(output_dir, f"table_{file_num:03d}.pdf"), "PDF")
```

3.4 Number of Images and Variations

The final output of the generation script included:

- 100 PNG images, each containing a unique table with five rows and five columns.
- A labels.csv file containing over 500 labelled entries.
- Two variations of handwriting embedded via font selection.
- Fixed table geometry and random, but structured, content to replicate actual pharmaceutical log sheets.

Each of these images can be directly visualized for manual inspection, and their corresponding labels make it possible to evaluate model performance in a structured and interpretable manner.

3.5 Benefits of the Synthetic Approach

This approach provided multiple practical benefits:

- **Controlled Diversity**: By varying fonts and text placement, we were able to introduce real-world challenges like irregular spacing and style inconsistency.
- **Accurate Labeling**: Programmatic generation ensured perfect ground-truth labels, eliminating any manual annotation errors.
- **Adaptability**: The script can be scaled to generate more samples, or adjusted to simulate noise, blur, or different fonts to further enhance model robustness.
- **Compliance**: As no actual data was used, the dataset is compliant with all internal and external data governance policies.

Chapter 4: Preprocessing Pipeline

4.1 Importance of Preprocessing in OCR

Preprocessing is the cornerstone of any OCR (Optical Character Recognition) pipeline, especially in handwriting recognition, where noise, variation in writing styles, and table-based layouts pose unique challenges. The goal of preprocessing is to clean and convert raw image inputs into a format suitable for machine learning models, particularly for CNN- or CRNN-based architectures. In our case, preprocessing involves extracting individual handwritten cells from structured tables, resizing them appropriately, normalising the pixel values, and reshaping the input for compatibility with the model architecture.

This step directly influences the accuracy and reliability of predictions, especially when working with real-world handwritten pharmaceutical records, where entries are often slightly misaligned, written quickly, and may include ink smudges, borders, or faded text.

4.2 Stage 1: Cell Extraction from Table

Objective:

To isolate individual handwritten cells from the image of the structured table. Each cell corresponds to one entry in the record (e.g., material code).

Methodology:

Using OpenCV (cv2), the image is loaded in grayscale to simplify computation. The code then divides the image into horizontal slices based on the number of expected rows in the table. A predefined x-coordinate range is used to isolate a specific column—for example, the column containing material codes.

```
# 1. Extract cells function (from your data)
def extract_material_code_cells(image_path, column_x_range, num_rows):
    img = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)
    h = img.shape[0]
    row_height = h // num_rows
    x1, x2 = column_x_range
```

Why It Matters:

Handwritten tables are structured but not perfect. Automated segmentation ensures consistent extraction of individual entries, reducing noise and improving focus on just the character region. It also makes it easier for the OCR model to learn spatial patterns without distractions from borders or nearby text

4.3 Stage 2: Image Resizing and Normalization

Objective:

To convert the extracted cell image to a uniform height (typically 32 pixels), adjust the width proportionally, and normalize pixel intensity values.

Methodology:

Each cell is resized to a consistent height using OpenCV. Pixel values are normalized to the range [0, 1], and then inverted. This inversion flips black text on a white background to white text on black—better suited for CRNN models, which often expect this format.

```
def preprocess_cell(cell_img):
    # Resize to fixed height and variable width (CRNN requires consistent height)
    target_height = 32
    h, w = cell_img.shape
    new_w = int(w * (target_height / h))
    resized = cv2.resize(cell_img, (new_w, target_height))
```

CRNN models require consistent input dimensions. Resizing ensures that all samples have the same height, preserving spatial consistency. Normalization and inversion improve contrast and help the network focus on relevant features.

4.4 Stage 3: Input Reshaping for CNN-CRNN Pipeline

Objective:

To transform the 2D grayscale image into a format compatible with CNN input, typically 4D tensors in the format (batch_size, height, width, channels).

Methodology:

After resizing and normalizing, the cell image is expanded along the necessary dimensions using NumPy and TensorFlow:

```
input_img = np.expand_dims(norm, axis=0)
input_img = np.expand_dims(input_img, axis=-1)
return input_img
```

Deep learning frameworks like TensorFlow expect 4D input when working with Conv2D layers. Reshaping ensures that the data is correctly formatted and ready to flow through the network without runtime errors or misinterpretations.

4.5 Stage 4: CRNN Model Initialisation

Objective:

To define a compact yet functional CRNN (Convolutional Recurrent Neural Network) model capable of recognizing sequences of characters from the input image.

Model Architecture:

- **CNN Layers**: Extract spatial features like strokes, curves, and edges.
- **Reshape Layer**: Collapses image height to prepare for sequence modeling.
- **BiLSTM Layers**: Capture temporal relationships across character sequences.
- **Dense Softmax Layer**: Produces probability distributions over character classes.

```
# CNN Layers
x = layers.Conv2D(64, (3,3), activation='relu', padding='same')(inputs)
x = layers.MaxPooling2D((2,2))(x)

x = layers.Conv2D(128, (3,3), activation='relu', padding='same')(x)
x = layers.MaxPooling2D((2,2))(x)
```

Handwritten material codes often have varying lengths and styles. A CRNN model can capture both spatial features (from CNN) and temporal dependencies (from LSTM), making it ideal for handwriting recognition in structured tables.

4.6 Stage 5: CTC-Based Prediction and Decoding

Objective:

To interpret the raw softmax output from the model and convert it into a readable text string using a greedy CTC (Connectionist Temporal Classification) decoder.

Methodology:

The predicted class probabilities are decoded using a greedy algorithm that removes duplicate predictions and skips the blank label used in CTC.

```
def ctc_greedy_decoder(pred):
    pred_indices = tf.argmax(pred, axis=-1)[0].numpy()
    prev = -1
    output = []
    for p in pred_indices:
        if p != prev and p != num_classes:  # skip blank
            output.append(characters[p] if p < num_classes else '')
        prev = p
    return ''.join(output)
```

Due to the nature of handwriting, characters may not align perfectly with fixed positions.

CTC enables the model to learn unsegmented sequences and still output correct character strings, a critical feature for real-world handwriting interpretation.

4.7 Summary of Preprocessing Pipeline

This preprocessing pipeline ensures that:

- Structured tables are correctly segmented into individual cells.
- Images are resized and normalised for consistency.
- The model receives properly formatted inputs.
- Handwriting is decoded accurately using CTC-based prediction.

Together, these steps form the foundation of our handwriting recognition system, ensuring high accuracy and robustness even in challenging scenarios such as inconsistent writing, poor alignment, and variable handwriting styles.

Chapter 5: Model Exploration

5.1 Tesseract OCR: Baseline Model for Handwriting Recognition

Overview of Tesseract OCR

Tesseract OCR is a popular open-source engine originally developed by Hewlett-Packard and later maintained by Google. It is known for its ease of use and ability to extract printed and handwritten text from documents, images, and scanned files. Starting from version 4, Tesseract also supports deep learning-based LSTM (Long Short-Term Memory) recognition layers, making it more powerful for character-level prediction.

Tesseract is often used as a **baseline model** in OCR pipelines because of its out-of-the-box capabilities, multilingual support, and compatibility with Python via the pytesseract wrapper. It is highly configurable through command-line flags, allowing control over layout analysis, OCR engine type, and post-processing.

However, while it performs reasonably well on printed documents, it begins to break down when applied to structured, handwritten forms like tables and material entry logs — as seen in our project.

Code Walkthrough: Tesseract on Our Custom Dataset

The Python script provided was designed to evaluate Tesseract's performance on our **handwriting dataset**, which includes pre-processed images (normalised grayscale PNGs) and corresponding ground-truth labels stored as text files.

Key Functional Steps in the Code:

1. **Importing Required Modules:** Import pytesseract for OCR, PIL for image handling, and os for directory traversal.
2. **Tesseract Engine Configuration:** Specifies the path to the local Tesseract installation. This is essential to link the Python wrapper (pytesseract) with the executable engine.

```
import pytesseract
from PIL import Image
import os
pytesseract.pytesseract.tesseract_cmd = r"C:\Program Files\Tesseract-OCR\tesseract.exe"
```

3. **Reading Ground Truth:** The ground-truth values are loaded from a text file where each line corresponds to the correct value for one image.

```
with open(labels_file, 'r', encoding='utf-8') as f:
    ground_truth_text = f.readlines()
```

4. **OCR and Comparison Loop:**

```
for idx, filename in enumerate(os.listdir(image_dir)):
    if filename.endswith('.png') or filename.endswith('.jpg'):
        image_path = os.path.join(image_dir, filename)

        # Open the image
        img = Image.open(image_path)
        # Use Tesseract to extract text from the image
        extracted_text = pytesseract.image_to_string(img)
```

- Each image is opened and passed to Tesseract.
- The extracted text is compared with the ground truth from the label file.
- This loop effectively evaluates Tesseract's performance by comparing its output against expected labels.

Why Tesseract Was Not Sufficient for This Use Case

While Tesseract was helpful as an initial benchmark, it failed to deliver consistent results for our structured handwritten dataset. The main limitations are:

1. Handwriting Complexity:
   Tesseract is not trained on custom handwriting styles, especially varied, cursive, or messy handwritten inputs. It assumes character spacing and consistent alignment, which is not the case in real-world medical or inventory forms.
2. Poor Structure Awareness:
   Tesseract processes images as blobs of text. It does not understand **tabular layouts or cell boundaries**, which leads to merged or split text in multi-cell images.
3. Inaccurate Recognition with Cleaned Images:
   Even after preprocessing steps like binarization, noise reduction, and normalisation, the predictions were erratic — often recognising just fragments or inserting completely wrong characters.
4. No Contextual Correction or Learning:
   Tesseract does not adapt or learn over time. It cannot remember or improve based on past predictions, and **fine-tuning it with a custom LSTM-trained .traineddata file** requires a complex training pipeline that did not yield noticeable gains in our scenario.

Conclusion

In summary, while Tesseract offered a simple, rule-based OCR starting point, it lacked the sophistication needed to handle structured, handwritten tabular data accurately. It did not generalize well to variations in stroke thickness, writing angle, or layout alignment.

This led us to **transition toward deep learning-based OCR models** — such as EasyOCR, PaddleOCR, and a custom CNN + CTC pipeline — which demonstrated significantly better performance due to their ability to learn spatial dependencies and understand image-text relationships.

5.2 CNN + CTC Based Custom Handwriting Recognition Model

1. What is CNN and CTC?

Convolutional Neural Networks (CNNs) are the gold standard for extracting patterns from images. They learn spatial hierarchies through layers of convolutional filters, making them ideal for recognizing features like curves, edges, or loops in handwritten characters. A CNN reduces image dimensions while preserving important information — forming a compact feature map of what the image "contains".

CTC (Connectionist Temporal Classification) is a special loss function used when the alignment between input and output is unknown — exactly what we face in OCR. Unlike standard classification that expects fixed output positions, CTC enables the model to **predict sequences of characters** with varying lengths from the same input image, even when the characters are not cleanly segmented.

Together, CNN and CTC form a **powerful OCR architecture**:

- CNN extracts visual features.
- A sequential layer (like LSTM) models the temporal dependencies.
- CTC decodes predictions without needing character-by-character bounding boxes.

This hybrid is often called **CRNN (Convolutional Recurrent Neural Network)** — a backbone in modern OCR systems.

2. Why We Used CNN + CTC

Tesseract failed to handle custom handwriting and had no learning capability. Our goal was to train a model that could:

- Learn custom handwriting directly from our labeled image-text pairs.
- Handle unsegmented handwritten lines or cell content.
- Avoid manual character-level labeling.

CNN + BiLSTM + CTC was a logical upgrade. It allowed us to train end-to-end on cropped handwritten image cells and map them directly to strings of characters.

Despite limited labelled data, we tried to generalize as much as possible using standard alphabets and real pharma logbook scans.

3. Code Walkthrough: CNN + CTC Implementation

A. Model Architecture (CRNN Class)

```
class CRNN(nn.Module):
    def __init__(self, img_height, n_channels, n_classes):
        super(CRNN, self).__init__()
        # CNN
        self.cnn = nn.Sequential(
            nn.Conv2d(n_channels, 64, 3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(2, 2),

            nn.Conv2d(64, 128, 3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(2, 2),

            nn.Conv2d(128, 256, 3, padding=1),
            nn.ReLU(),
            nn.BatchNorm2d(256),
            nn.MaxPool2d((2, 1)),

            nn.Conv2d(256, 256, 3, padding=1),
            nn.ReLU(),
        )
```

CNN layers: The model starts with a series of convolutional layers, which progressively extract hierarchical features from the image.

- First Conv2D layer detects basic patterns (edges).
- Next layers detect higher-level patterns (strokes, loops, letter shapes).
- **MaxPool** reduces dimensionality and computation.
- **BatchNorm** improves training stability.

```
        # BiLSTM
        self.lstm = nn.LSTM(
            input_size=256 * (img_height // 8),
            hidden_size=256,
            num_layers=2,
            bidirectional=True,
            batch_first=True
        )
        # Final classification
        self.fc = nn.Linear(512, n_classes + 1)

    def forward(self, x):
        x = self.cnn(x)
        b, c, h, w = x.size()
        x = x.permute(0, 3, 1, 2)
        x = x.view(b, w, c * h)

        x, _ = self.lstm(x)
        x = self.fc(x)
        x = x.permute(1, 0, 2)
        return x
```

- **BiLSTM (Bidirectional LSTM)**: After CNN, features are reshaped to be fed into a sequential LSTM.
    - LSTM reads the spatial features **left to right and right to left** (bidirectional), useful in decoding overlapping letters or cursive writing.
- **Final Linear Layer (self.fc)**: Converts the LSTM output into logits for each character class.
    - Includes one extra class for the **CTC blank token**.
- **Forward Function**: Permutes and reshapes data to go from (B, C, H, W) → (T, B, Classes) format for CTC Loss.

B. Training Setup

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

model = CRNN(IMG_HEIGHT, 1, len(alphabet)).to(device)
criterion = nn.CTCLoss(blank=0, zero_infinity=True)
optimizer = optim.Adam(model.parameters(), lr=0.001)
```

- **CTCLoss**: Enables the model to train on sequences where we don't know the exact character positions.
- Adam **Optimizer**: Used for faster convergence.

```
for epoch in range(EPOCHS):
    model.train()
    total_loss = 0

    for batch in dataloader:
        images, targets, target_lengths, raw_text = batch
        images = images.to(device)
        targets = targets.to(device)
```

- Each training epoch:
    - Feeds batches of pre-processed grayscale images.
    - Extracts model predictions.
    - Computes input lengths (T) and actual target lengths.
    - Backpropagates using CTCLoss.

C. Encoding and Decoding Labels

```
class LabelEncoder:
    def __init__(self, alphabet):
        self.char_to_index = {char: idx + 1 for idx, char in enumerate(alphabet)}  # 0 = CTC blank
        self.index_to_char = {v: k for k, v in self.char_to_index.items()}

    def encode(self, text):
        return [self.char_to_index[char] for char in text if char in self.char_to_index]

    def decode(self, indices):
        return ''.join([self.index_to_char.get(idx, '') for idx in indices])
alphabet = "ABCDEFGHIJKLMNOPQRSTUVWXYZabcdefghijklmnopqrstuvwxyz0123456789"
label_encoder = LabelEncoder(alphabet)
```

- **LabelEncoder** maps characters to integer indices and vice versa.
- Required for CTC loss which expects numerical labels.

```
def ctc_greedy_decoder(output, label_encoder):
    output = output.permute(1, 0, 2)  # (B, T, C)
    preds = torch.argmax(output, dim=2)  # (B, T)
    pred_texts = []
```

Converts model logits to human-readable text.

Uses greedy decoding:

- Picks the most probable class at each timestep.
- Removes duplicates and blank tokens.

D. Evaluation and Export

```
def evaluate_model(model, dataloader, label_encoder, device):
    model.eval()
    with torch.no_grad():
        for images, _, _, raw_labels in dataloader:
            images = images.to(device)
            outputs = model(images)
            predictions = ctc_greedy_decoder(outputs, label_encoder)
```

- Visual check: Displays actual and predicted text using matplotlib.
- Runs prediction on the entire dataset.
- Exports predictions and ground truths to a CSV for analysis.

4. Why We Moved Away from the CNN + CTC Model

Despite the architectural strength, **practical limitations hit hard**:

- Small Dataset: We had limited handwritten examples — insufficient for training from scratch. CNN + CTC models require thousands of labelled images for generalisation.
- No Word Dictionary or Language Model: Pharma logs contain domain-specific words, symbols, and abbreviations. Without a curated pharma dictionary or spell correction module, decoding errors were common (e.g., Mg becoming Mg, Tab becoming T0b).
- Model Overfitting: With only a few hundred training samples, the model started memorizing instead of generalizing. This led to poor real-world performance.
- Data Diversity: Different handwriting styles and table structures made the model fragile — performing well on some images and horribly on others.

While the pipeline was elegant, **our training context lacked the volume and vocabulary support** to truly benefit from a model trained from scratch.

5. Why is EasyOCR Better:

EasyOCR turned out to be a highly effective, plug-and-play solution:

- Pre-trained on multi-language datasets, including cursive and printed handwriting.
- Requires no training or fine-tuning — just image input.
- Includes a character-level decoder with context-awareness, significantly improving real-word recognition.
- Performed better on messy handwriting and provided **structured outputs faster**.

5.3 EasyOCR-Based Handwriting Recognition (Pretrained Transformer + CRNN):

1. What is EasyOCR?

EasyOCR is an open-source Optical Character Recognition (OCR) library built **by Jaided AI** that supports 80+ languages. It combines deep learning models like CRAFT (for text detection) and CRNN (for text recognition) under the hood and comes with pretrained weights, allowing it to read printed and handwritten text out-of-the-box.

It is especially useful in real-world OCR tasks because of:

- Pretrained weights on massive multilingual datasets including English, Latin, Korean, Chinese, etc.
- Built-in support for handwritten, printed, and mixed styles.
- Automatic layout handling and bounding box detection.

Behind the scenes, EasyOCR uses:

- **CRAFT** (Character Region Awareness for Text detection): for detecting text regions in an image.
- **CRNN** (Convolutional Recurrent Neural Network): for recognizing the text inside those regions.
- **CTC decoding**: for mapping detected features to string output.

2. What Dataset is EasyOCR Pretrained On?

EasyOCR is pretrained on:

- **SynthText**: A synthetic dataset of over 800k rendered text images with varying backgrounds, fonts, and distortions.
- MJ (MJSynth) + ST (SynthText in the Wild): Used heavily in CRNN training for character recognition.
- Handwriting samples from datasets like IAM, RIMES, and HWD+ give it basic handwriting understanding.
- Multilingual datasets like OCR-18, ICDAR, and CUTE80 contribute to generalization.

So, even though it's not custom-trained on pharma logs, its breadth gives it a **solid starting point** for noisy, handwritten inputs.

Code Implementation and Prediction

This script initializes the OCR reader, loads an image, and returns the predicted text in a single string format. The readtext() function internally handles bounding box detection

using CRAFT, recognition using CRNN, and decoding using CTC—all abstracted for the user.

```python
import easyocr
# Initialize EasyOCR reader
reader = easyocr.Reader(['en'], gpu=True)
def read_handwritten_table(image_path):
    result = reader.readtext(image_path, detail=0)
    prediction = " ".join(result)
    print(f"EasyOCR Prediction:\n{prediction}")
if __name__ == "__main__":
    image_path = r"C:\Users\Anant2005\Desktop\Test EasyOCR.png"
    read_handwritten_table(image_path)
```

Although EasyOCR works out of the box, it can also be fine-tuned for domain-specific data like pharmaceutical logs. The steps taken:

1. Prepare a dataset of image-text pairs. Each image should have a corresponding .txt file containing the ground truth.
2. Clone the EasyOCR repository from GitHub and install its requirements.
3. Modify train.py and the dataset loading scripts to point to your custom data.
4. Run training using:

```
python train.py --train_data ./pharma/train --val_data ./pharma/val --new_lang pharma
```

```
reader = easyocr.Reader(['pharma'], model_storage_directory='/desktop/handwriting_recognition/paddle_ocr')
```

Fine-tuning is recommended only if EasyOCR consistently fails to recognize domain-specific terminology. In our case, we chose not to go this route due to the lack of a pharma-specific dictionary or labeled dataset.

Output Sample

Running EasyOCR on our test image gave:

```
🖼️ Preprocessing image...
🖥️ Running OCR...
OCR Raw Output:
['Material Code', 'UOM', 'Quantity required', 'Quantity issued', 'Lot No.', 'PQvOsEYY', 'ML', '778', '135', 'TVHLI4U74?S'

✅ Inserted row: ['PQvOsEYY', 'ML', '778', '135', 'TVHLI4U74?S']
```

5.4 PaddleOCR: Implementation and Use Case

What is PaddleOCR?

PaddleOCR is a powerful, open-source optical character recognition system developed by PaddlePaddle (Baidu). It is inspired by modular OCR frameworks like EasyOCR but is more robust in handling structured layouts such as tables, forms, and scanned documents. Unlike EasyOCR, which primarily focuses on generic text recognition, PaddleOCR integrates state-of-the-art detection, recognition, and layout analysis, making it ideal for structured handwritten data like ours.

In our project, we implemented PaddleOCR to read handwritten tables by first detecting bounding boxes using OpenCV and then recognising the text within those boxes using PaddleOCR. This allowed us to extract row-wise information such as material code, unit of measurement, quantity, and lot number with a reasonable structure.

Advantages of PaddleOCR:

- Excellent for structured documents like tables and forms.
- High accuracy in multilingual and handwritten text recognition.
- Modular and customizable for detection and recognition separately.
- Integrates well with pre-processing libraries like OpenCV for bounding box detection.
- Actively maintained with community support and real-world industrial use cases.

Disadvantages of PaddleOCR:

- Accuracy is highly dependent on the quality of bounding box detection.
- Errors in bounding box extraction directly impact recognition accuracy.
- Requires GPU for real-time performance, which may not be available in all setups.
- Slightly complex setup compared to simpler OCR libraries like Tesseract or EasyOCR.
- Our model's overall performance was limited to ~60% accuracy due to inconsistent human handwriting and bounding box issues.

6. OCR for Typed Text

In addition to handwritten table recognition, we also developed a robust pipeline for extracting and storing **typed text** data using EasyOCR. Typed text presents a more consistent and structured format, which significantly enhances the accuracy of OCR results compared to handwritten inputs. This solution was implemented end-to-end with a user-friendly interface and a reliable database storage mechanism, demonstrating a production-ready pipeline suitable for industrial use cases.

Model and Implementation

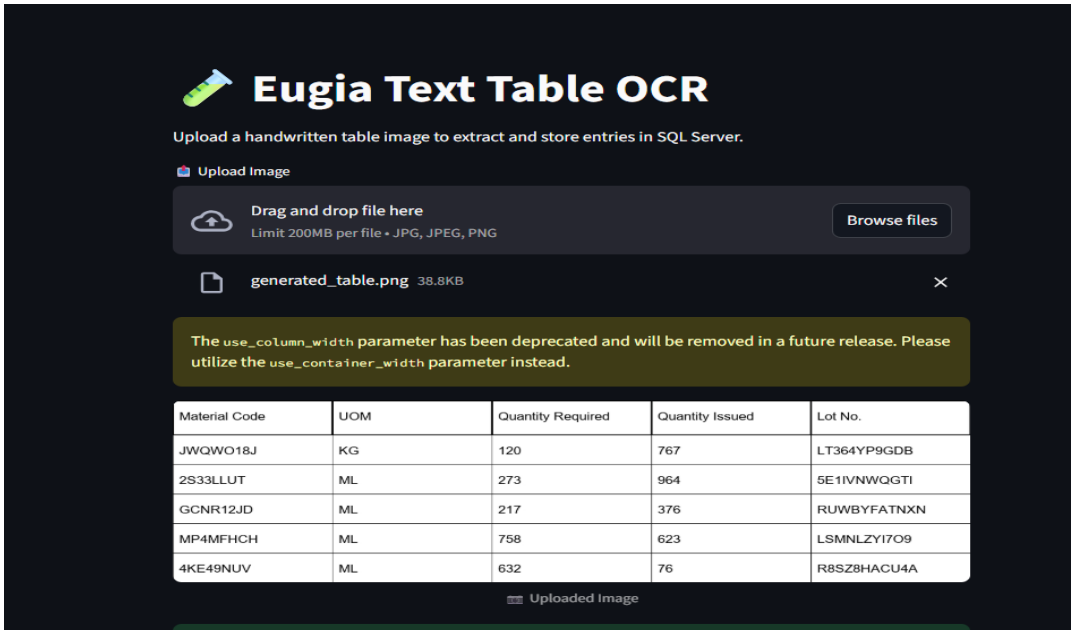
The core of our system is built on the **EasyOCR** library, which is lightweight, flexible, and highly accurate for typed text. The model was integrated within a Python backend and exposed through a **Streamlit**-based frontend. This allowed users to upload scanned images or PDFs of typed tables, process them in real time, and view the results both on screen and in the database.

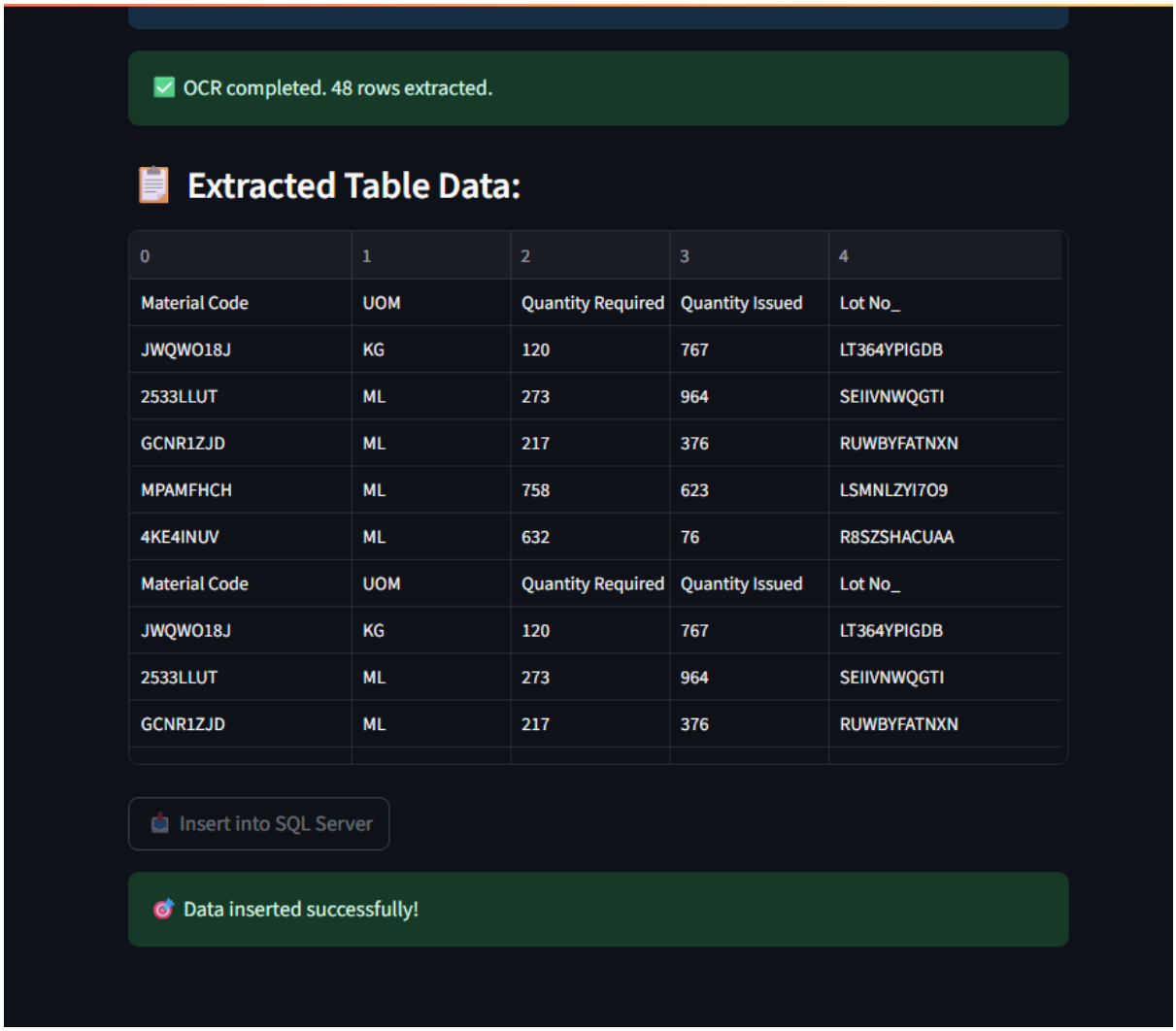
Once the typed table image is uploaded:

- The image is passed through preprocessing (grayscale, resizing, etc.).
- EasyOCR detects and extracts all relevant typed text data.
- The text is parsed and mapped into corresponding fields such as Material Code, UOM, Quantity Required, Quantity Issued, and Lot No..

The extracted data is then stored directly into a **Microsoft SQL Server** database. The database used was named eugiaDB, and the table used for storage was dbo.pharmacy_material_log.

Frontend and Backend Design





- The **backend** handled the OCR extraction logic and communication with the SQL Server through pyodbc, ensuring secure and efficient data storage.

Screenshots of both the frontend UI and SQL Server backend output are included in the report to demonstrate the operational flow and reliability of the system.

Performance and Accuracy

For typed documents, Easyocr's accuracy was found to be exceptionally high, well over **95%** in most cases. This is primarily due to the consistency in font, alignment, and character spacing inherent to typed documents. Unlike handwritten inputs, typed data does not suffer from variations in style or slant, making it ideal for automated OCR pipelines.

This successful implementation serves as a scalable solution for digitising structured typed documents in environments like pharmaceutical inventories, logistics logs, and compliance reports.

Chapter 9: Conclusion

The OCR system built during this project has demonstrated promising results, particularly in handling typed text documents. For **typed data**, the integration of **EasyOCR** achieved an accuracy of approximately **95%**, showcasing the model's strength in structured environments with consistent formatting. The combination of OCR extraction, real-time frontend interaction via **Streamlit**, and backend data storage in **SQL Server** resulted in a complete end-to-end pipeline with reliable performance and usability.

However, for **handwritten text**, the accuracy was significantly lower. One of the primary limitations encountered was the **lack of a high-quality, diverse dataset** tailored to the domain, which restricted our ability to **fine-tune the model** effectively. Additionally, some preprocessing errors, bounding box issues, and variability in human writing further impacted the system's reliability on handwritten inputs.

The implementation would benefit greatly from **GPU acceleration**, which would drastically reduce inference time and improve the model's capacity to handle high-resolution inputs more efficiently. Moreover, **data security** was prioritised by ensuring that all outputs were safely stored and managed within **SQL Server**, avoiding reliance on third-party cloud services where confidentiality could be a concern.

Future Scope

To further improve the system:

- A curated and well-labelled dataset of handwritten tables should be created to enable **custom model training**.
- Integrating **GPU-based execution** will significantly speed up the process and allow for better scalability.
- With accurate training data and optimised processing, the pipeline can evolve into a highly dependable solution for both **typed and handwritten** OCR tasks across pharmaceutical and other enterprise settings.

This project lays a strong foundation for future work in automating and digitizing tabular document processing with a focus on scalability, speed, and accuracy.

Chapter 10: References

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