





Rachit Jain Chloe Wu Candidates of Master of Business Analytics, MIT

CAPSTONE PROJECT

Document Classification Capability

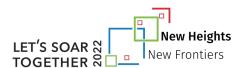
Revving up manual paperwork with Computer Vision & NLP

MIT x Wolters Kluwer

Faculty Advisor: Dr. Ilya Jackson

WK Advisors: Pooja Srivastava & Varun Dixit

18th August 2023



Agenda

Introduction

Overview

Challenges

Motivation



The Process

Solution

Methodology

(Re-labelling, Modelling)



Results

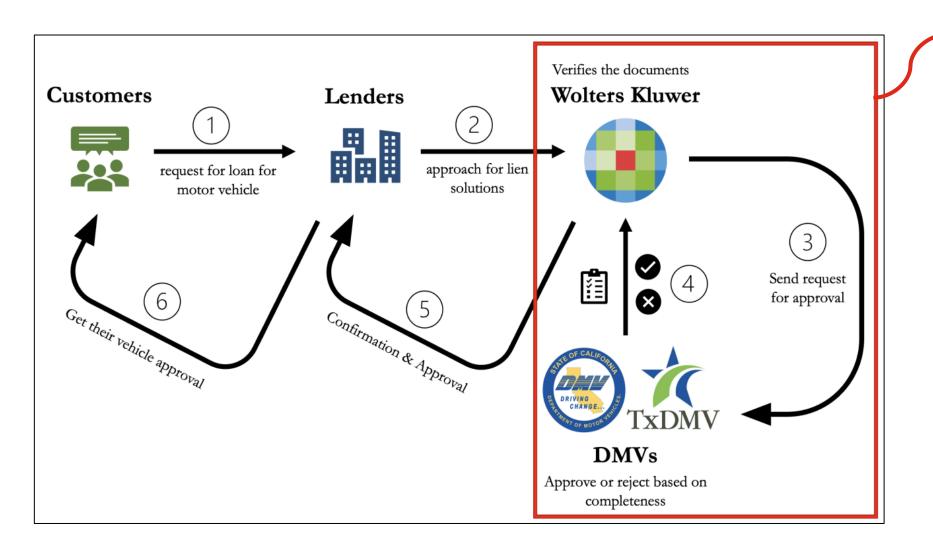
Demo

Deliverables

Impact & Business Value



Overview | Motor Vehicle registration process is error-prone



Challenges At Scale 🍣

Huge Volume

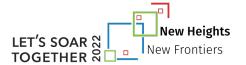
50k+ pages¹ per day

Multiple rejections

10% rejection rate

High processing time

10 mins per request (~20 pages)



Challenges | Manual processing is a bottleneck

Challenges At Scale

50k+ pages¹ per day

Huge Volume

10%

rejection rate

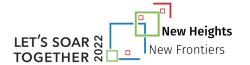
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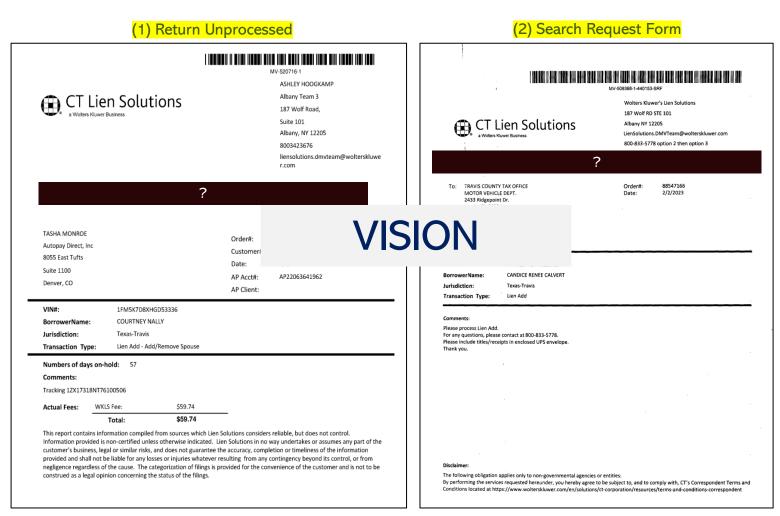


Build an automated, generalized document classification capability to make historically manual logistics paperwork easier to execute and more accurate

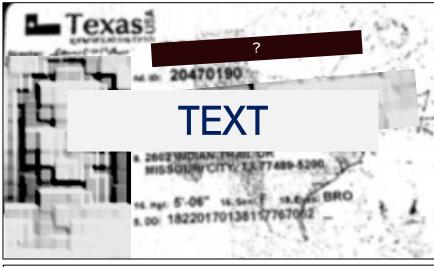


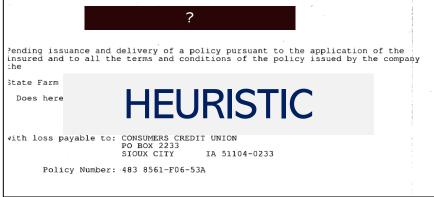
Motivation | Need for more than rule-based systems

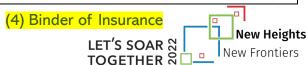
Similar formats, similar text, but different titles



(3) Identification Card



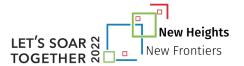




Our Solution



- Document Classification Capability
- Capstone of the Year? 😥



Imbalanced dataset across 120+ categories; 12k scanned pages

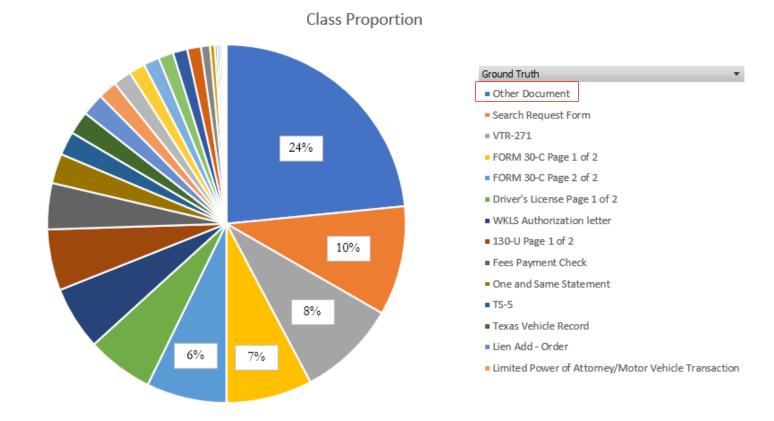
Training Data

12k+

Data Points

10k+

from top 31 classes

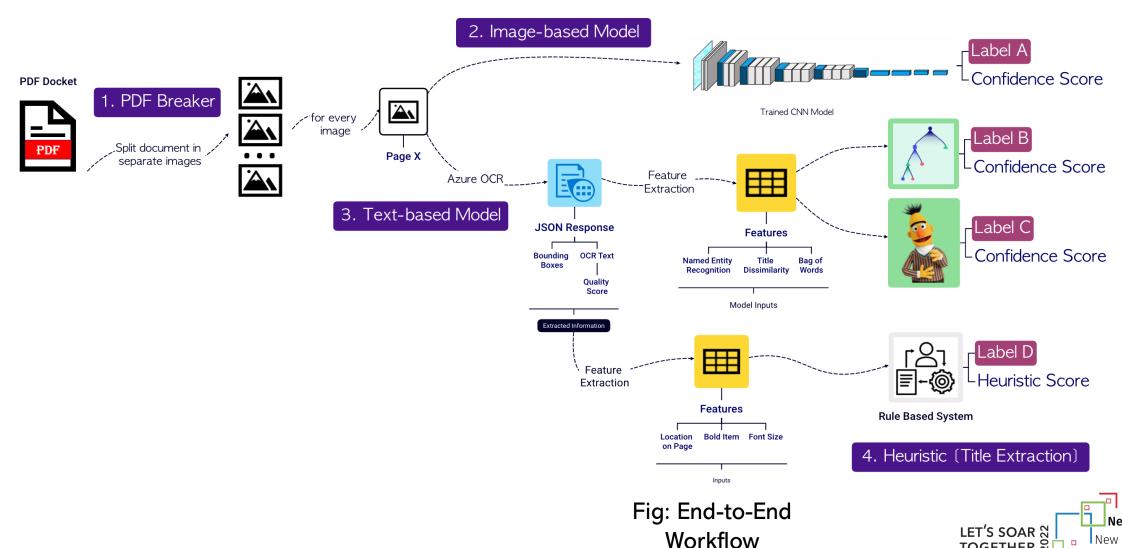


Represented Counties:

Bexar, Brazoria, Dallas, El Paso, Fort Bend, Harris, Hidalgo, Lubbock, Travis, Van Zandt



Solution | End-to-End Workflow takes PDF input and gives multiple labels for each page, along with confidence scores



Step 0: Need for relabeling - Mystery behind ground truth labels

Status Quo

Current 'Ground Truth' Label = Output of Champion model

Wrong Labels → Poor Models

Solution?

'Smarter' Manual Labelling
[Unsupervised Clustering on Deep Embeddings]

- Cluster similar image embeddings from trained vision model
- Merge clusters on common categories & create sub-clusters
- Smarter Manual Label

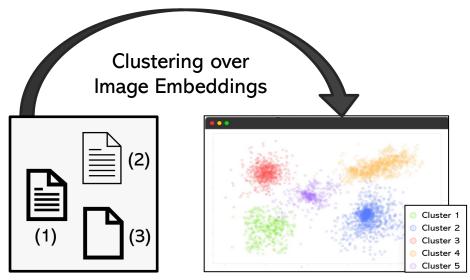


Fig: Embeddings for each image clustered based on similarity

Results

88% saving in time for

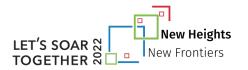
manual labelling

10.6%

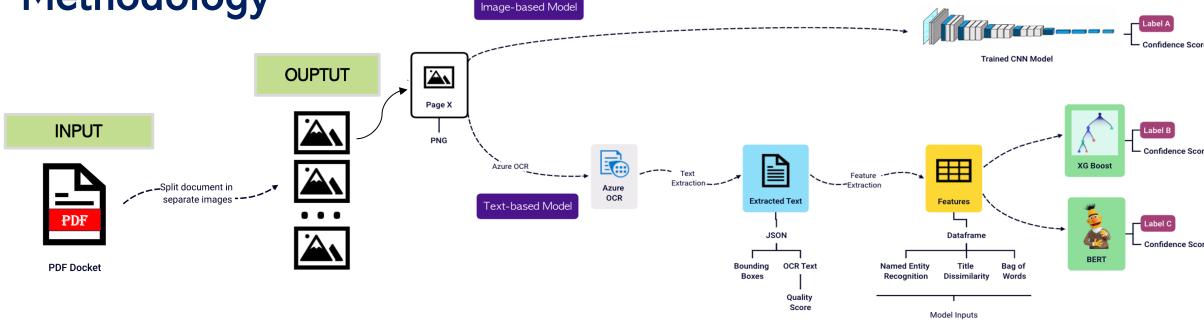
Mis-classified labels identified

8%

F1 Score jump!



Methodology



1) PDF Breaker API

PDF Breaker on a Streamlit dashboard

Each page is extracted as an image and saved in folders

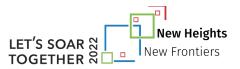
2 Vision-based Model

CNN model fine-tuned on 12k scanned documents

(3) Text-based Model

BERT + XGBoost running on text extracted from AzureOCR

<u>Highlights</u>: Image padding, Image processing, Hyper-parameter tuning, Data Augmentation, Feature Engineering...



Methodology

1 PDF Breaker API

PDF Breaker on a Streamlit dashboard

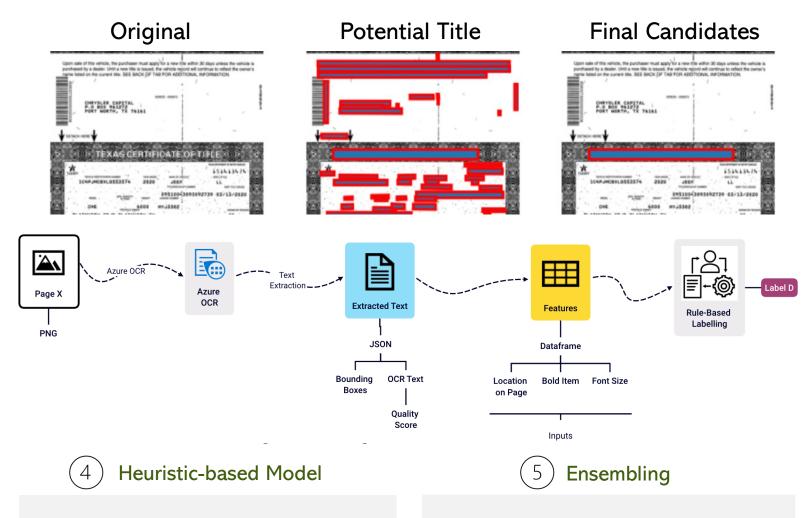
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(2) Vision-based Model

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Potential title extraction from any document type

Selecting 'supreme' model; if clash, choose heuristic



The labels need to be ensembled into one single prediction

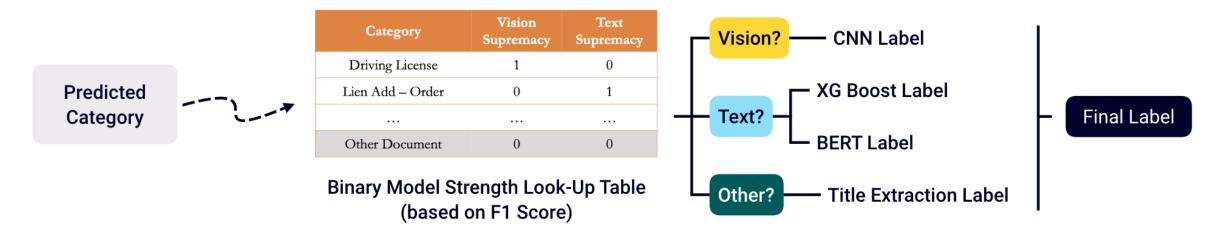


Fig: Logic workflow to combine the labels

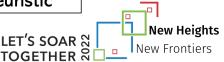
Our Implementation

Model Supremacy for Vision and Text based models

Training F1 score used to assign 'supreme' model for each category

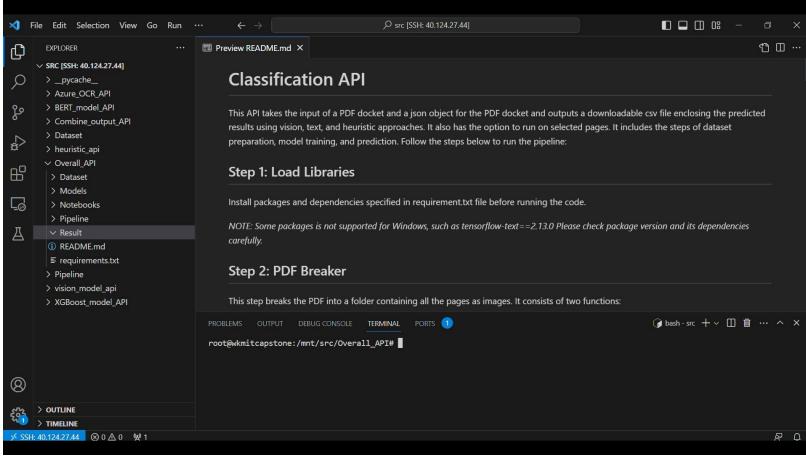
Ensemble Technique

| Case | Same Label | Vision Supermacy? | Text Supremacy? | Final Model |
|--------|------------|----------------------|--------------------|---------------|
| Case 1 | 1 | 1 | 0 | Same |
| Case 2 | 0 | 1 | 1 | Manual Review |
| Case 3 | 0 | 1 | 0 | Vision |
| Case 4 | 0 | 0 | 1 | Text |
| Case 5 | 1 | 0 | 0 | Heuristic |



Result | End-to-End multi-modal architecture deployed





Video: Demo implemented over FastAPI and deployed over WK's Virtual Machine



Deliverables | Scalable model pipeline deployed over WK Cloud

Result Summary



0.86

F1 Score

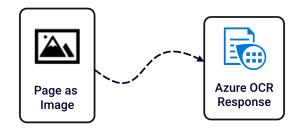
Over 31 document types over 2.1k highly noisy test dataset



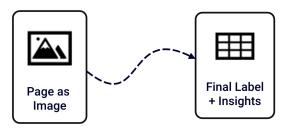
Our implementation beats the status quo with 5% higher F1 score

Our Deliverables to Wolters Kluwer

(1) OCR API



(2) CAPABILITY API



(3) Documentation & Knowledge Transfer

for smooth integration with current system

Learnings

Industry Practices





Dashboarding

Capability Design

Tech Stack







Business Skills





Business Value

Shareholders

10X growth

in business

Generalized capability → Scalable business model

Market Differentiation

Leveraging Al → journey to be market-leaders

Customers

3X lower

turn-around time

Less headache → Happy customers

70% lower

rejection rate

Quick and efficient → drives customer experience

Employees

10X faster

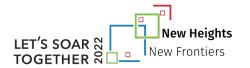
processing

Free from mundane work → higher productivity

Future-Ready

by leveraging Al

Machine aided human experts → Upskilling



High learning + Solid deliverables + Strong impact =

More ACCURATE Labelling

0.86 F1

High → Better

Flexible PDF BREAKER

Unrestricted

of PDFs broken

Result INTERPRETABILITY

User Insights

behind predictions

AUTOMATED pipeline

1 API

running everything

FEWER rejections

<u>∱</u>Y_åChallenger >

Champion (status-quo)

END-TO-END pipeline

Streamlined

workflow

LOW processing time

10X saving

in processing time

PRODUCTIONIZED pipeline

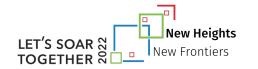
Deployed

over WK's VM

EASY-TO-INTEGERATE capability

Scalable

and reproducible









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Thank You!

Only those who will risk going too far can possibly find out how far one can go!

