

Designing Document Automation for a Changing AI Landscape

HOW TO STAY AHEAD OF THE CURVE



Summary

- ▶ The Intelligent Document Processing (IDP) landscape is undergoing significant change. Capabilities that were once proprietary—such as document extraction and classification—are increasingly available through hyperscalers, who are investing heavily in AI services that accelerate innovation and reduce barriers to adoption.
- ▶ As AI models continue to improve, accuracy scores and confidence thresholds are rising, minimizing the need for manual intervention. At the same time, organizations must support a broad mix of electronic content and remaining physical documents across an expanding range of document types. Strength across this diversity is becoming a key driver of reliable automation outcomes.



About this Session

Hosted by Kodak Alaris

- ▶ This session examines **how organizations can respond** to the ongoing race for AI by avoiding early commitment to a single technology or platform. **A future-ready automation strategy requires flexibility**—allowing organizations to adopt the most appropriate AI models as capabilities evolve, while maintaining governance, compliance, and operational control.
- ▶ **Attendees will gain practical insight** into building document automation programs where AI supports extraction and classification within a governed framework, rather than making autonomous business decisions. **The session will focus on architectural principles and strategic considerations** that help organizations remain adaptable, compliant, and prepared for continued change.



Key Takeaways

- ▶ How the role of proprietary extraction is changing in the IDP market
- ▶ Why hyperscaler-driven AI is influencing automation strategy and architecture
- ▶ The impact of higher accuracy and scoring confidence on manual processing
- ▶ The importance of supporting diverse document types and formats
- ▶ How model-agnostic approaches reduce risk and improve long-term flexibility
- ▶ Why governance remains essential as AI capabilities expand



Evolution in Intelligent Document Processing

The next AI wave is reshaping IDP.

Intelligent Document Processing

Intelligently extract, validate, and connect information into systems and processes

Enhancing with Generative AI



Leveraging
Large Language Models (LLM)



Specialized Models

Accurate data, better decisions & outcomes

- ✓ **Delegate** work to trusted AI
- ✓ Extract more information, accurately
- ✓ **Automate more** & Accelerate DX
- ✓ Deliver **greater insights** & understanding to drive decisions



How has technology evolved?



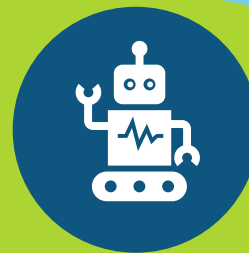
Phase 1

- Basic Document Management
- Scan, File, and Retrieve
- Light Workflow



Phase 2

- Accounts Payable Automation
- Electronic Forms
- Advanced Workflow



Phase 3

- Intelligent Document Processing
- Artificial Intelligence
- Machine Learning
- Robotic Process Automation
- OCR



Phase 4

- Visual Language Models (VLM)
- Intelligent Processing Automation (IPA)
- Agentic RAG
- MCP
- Chat AI



What has changed since the last AI+IM Global Summit?

▶ The Old Way

- ▶ Neural templating with Auto Learning
- ▶ Requires a knowledgebase, few shot
- ▶ Mapping Key-Value Pairs (KVP)
- ▶ Heavily reliant on OCR

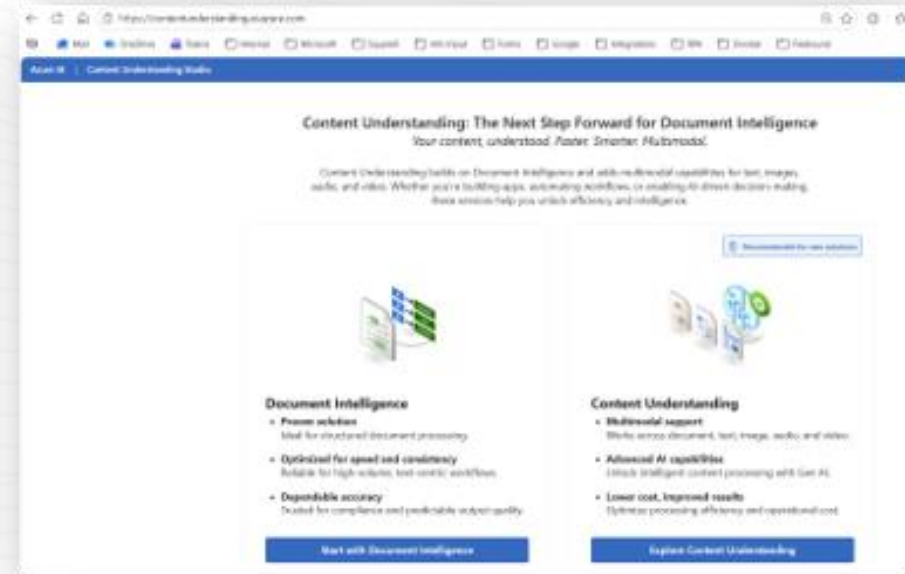
▶ The New Way

- ▶ LLM/Generative AI Prompting
- ▶ No knowledgebase, zero shot
- ▶ Uses NLP, visual queues and context to extract data more accurately NOT OCR
- ▶ Works better for unstructured content with no KVP



What you learned before has deprecated

- ▶ **Azure AI Document Intelligence** now replaced with **Azure AI Foundry/Content Understanding** using models
- ▶ Relying on OCR versus CONTEXT
- ▶ Cycling permutations of Key Value Pairs (KVP)
- ▶ Multi-model is required for most transactional processing
- ▶ Prevalence of Open Source models and self hosting for compliance
- ▶ Access to ground truth data for Fine tuning
- ▶ Concept of neural templates and auto learning vs fine tuning and modelbuilding



How did we used to do it?

▶ Neural template learning

- ▶ Azure AI Document Intelligence
- ▶ AWS Textract
- ▶ Google Document AI

▶ Define key value pairs

- ▶ Parse the JSON payload
- ▶ Add training and data set

▶ Mapping Key value pairs

- ▶ Default fields show in Source Fields from engine

▶ If engine does not find a match

- ▶ Requires significant JavaScript scripting

Workflow Step:
Name: OCR
Display name: Intelligent OCR
Activity: Intelligent OCR
Required Permission: [No Custom Permission]

Extraction Profile selection Queries Script Mappings Options

Minimum Confidence: 90.0

#	Min. Conf	Match Type	Source Field	Target Field	Tra
1	90	EXACT	VENDOR_NAME	VendorName	
2	90	EXACT	DUE_DATE	Terms	
3	90	EXACT	PIF-Amazon Textract Extraction Expt	InvoiceDate	
4	90	EXACT	INVOICE_RECEIPT_DATE	Tax	
5	90	EXACT	PIF-Amazon Textract Extraction Expt	SubTotal	
6	90	EXACT	INVOICE_RECEIPT_ID	InvoiceAmount	
7	90	EXACT	PIF-Amazon Textract Extraction Expt	PartNumber	
8	90	EXACT	PAYMENT_TERMS	Quantity	
9	90	EXACT	PIF-Amazon Textract Extraction Expt	UnitCost	
			PRICE		
			PIF-Amazon Textract Extraction Expt		
			QUANTITY		
			PIF-Amazon Textract Extraction Expt		
			RECEIVER_ADDRESS		
			PIF-Amazon Textract Extraction Expt		



Taylor believes that companies building their own models is **not a wise use of capital** unless they are an AGI research lab.

He views software development as an ongoing process that **requires continuous attention**, comparing it to a lawn that needs regular care.

“Software isn’t something you can create once and expect to work forever. In contrast, pre-training a model involves a significant, one-time cost, but once it’s done, the model can be used repeatedly for tasks like generating content.”

Models: Build vs. Buy

Ex-OpenAI Bret Taylor Says AI Is a Bubble — Companies Shouldn’t Build Their Own Models

OpenAI Chairman just said what we were all thinking...

- ▶ Building your own LLM data models and neural networks
 - ▶ Initial development costs and resources
 - ▶ Ability to get sample documents
 - ▶ Pivot with change in technology availability
- ▶ Wrapping IDP products around cloud engines
 - ▶ Focus on differentiators, UI and tools vs. underlying engine
 - ▶ OpenAi, AWS, Azure, Google



Why be boxed into a model?

▶ Speed of Change

- ▶ Models are changing monthly
- ▶ Lots of deprecation just when you launch a new project

▶ Performance

- ▶ Certain models perform better than other (e.g. Gemini 3.1)
- ▶ Certain models perform better with text, handwriting, video or audio differently, find the best model for the use case
- ▶ Model Routers – let the router pick the correct model

▶ Commercials & Costs

- ▶ Preview models are a lot more expensive, limited RPM (request per min)
- ▶ Open-source models are more cost effective and can be selfhosted

▶ Scalability

- ▶ Don't compete with hypervisor model building – they own the cloud infra and have billions of \$ to invest in R&D



Extractions Profiles - Additions

Difference in Cloud setup configuration

▶ AWS BDA

- ▶ More difficult to config in AWS
- ▶ Requires S3 buckets and IAM user get configured prior to BDA setup
- ▶ Requires access to BDA projects and blueprints in AWS to make changes

▶ OpenAI

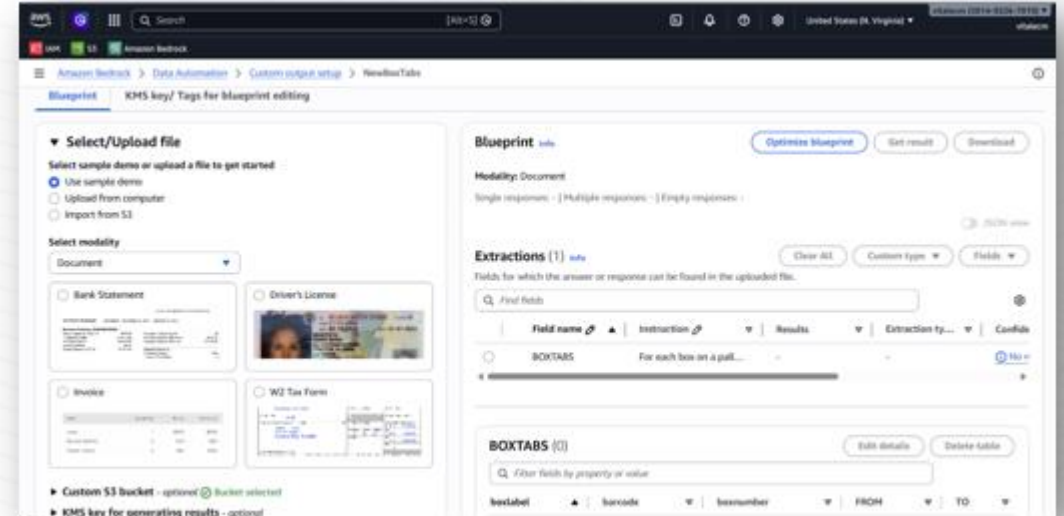
- ▶ Very easy to setup
- ▶ Simply create an organization and a project object

▶ Google Gemini

- ▶ Must enable Gemini for Google Cloud API

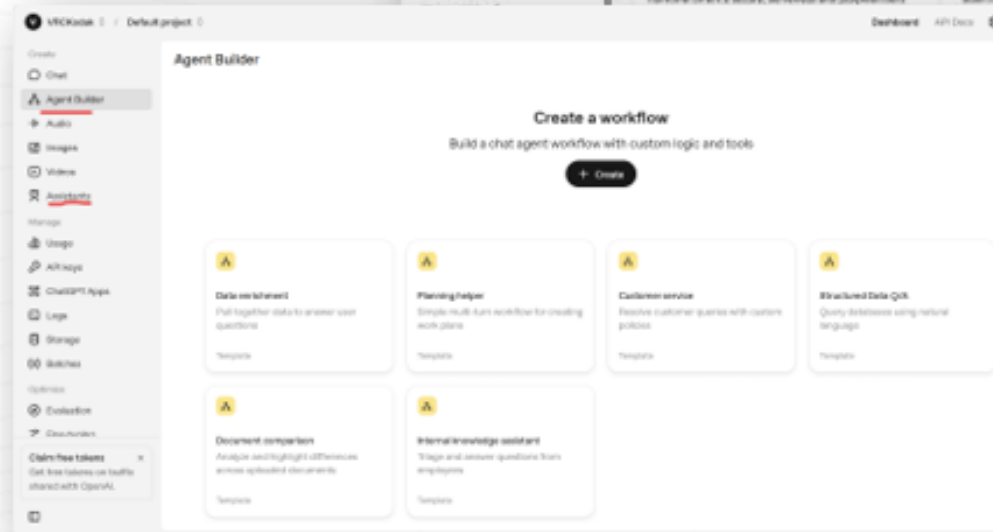
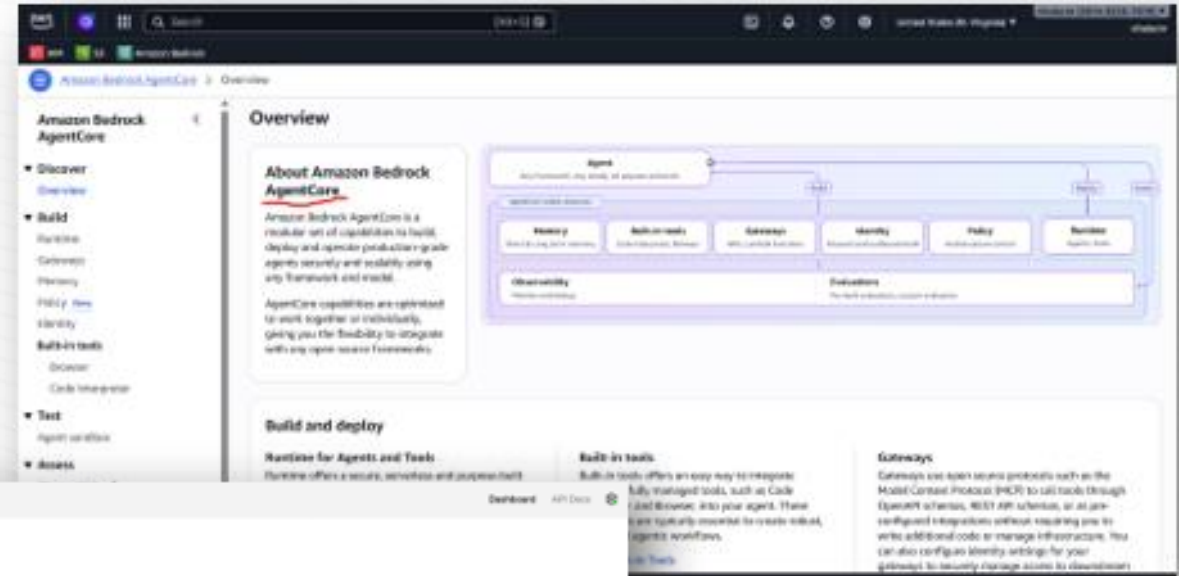
▶ Difference in setup configuration

- ▶ OpenAI – uses prompts for extraction
- ▶ Gemini– uses prompts for extraction
- ▶ AWS BDA – must create blueprints that generate key value pairs



Ecosystem Interoperability

- ▶ Pick the right cloud partner to extend beyond IDP
- ▶ The hypervisors are doing WAY more than model building
- ▶ Open Intelligence allows for any LLM model to be used as the "Intelligent Engine"
- ▶ Add-on products for:
 - ▶ Agentic AI
 - ▶ Reporting
 - ▶ Chat AI
 - ▶ AI Coding



How do we do it NOW?

▶ Generative AI/LLM Engines:

- ▶ OpenAI
- ▶ AWS BDA
- ▶ Google Gemini
- ▶ Box AI

▶ Define prompts:

- ▶ No training sets
- ▶ Using NLP to understand human questions into extractable content
- ▶ Visual context

▶ If no match

- ▶ Tweak the prompt

Extraction Profile selection Queries Script Mappings Options

You may add native language queries to be evaluated by the extraction profiles that support them

Name	Query text	Multi-value result
query_Seller	who is the seller of the loan	False
query_Bank	who is the bank	False
query_ABA	What is ABA routing number	False
query_AccountNumber	What is account number	False
query_Borrower	For each row, extract the borrower name o	True
query_NoteAmount	For each row, extract the note amount plac	True
query_LoanDate	For each row, extract the date shipped plac	True
query_Date	what is the date of the letter, looking at to	True
query_Buyer	Extract the company name that this letter i	False
query_LoanNumber	For each row, extract the loan number plac	True

Workflow Step:

Name: OpenAI

Display name: OpenAI

Activity: Intelligent OCR

Required Permission: [No Custom Permission]

Extraction Profile selection Queries Script Mappings Options

Minimum Confidence: 90.0

#	Min. Conf	Match Type	Source Field	Target Field	Tr
1	90	QUERY	query_Date: "what is the date of	Date	
2	90	QUERY	query_Seller: "who is the seller of	Seller	
3	90	QUERY	query_Bank: "who is the bank "	BankName	
4	90	QUERY	query_ABA: "What is ABA	ABA	
5	90	QUERY	query_AccountNumber: "What	AccountNumber	
6	90	QUERY	query_Borrower: "For each row,	BorrowerName	☰
7	90	QUERY	query_NoteAmount: "For each	NoteAmount	☰
8	90	QUERY	query_LoanDate: "For each row,	LoanDate	☰
9	90	QUERY	query_LoanNumber: "For each	LoanNumber	☰
10	90	QUERY	query_Buyer: "Extract the compan	Buyer	



Invoice Processing

Generative AI Voting

► Compare Results From:

- OpenAI
- AWS BDA
- AWS Textract
- Google Gemini
- ABBYYVantage
- Hyperscience
- Box.com AI
- Azure OpenAI



Line Items

PartNumber_A	Description_A	Quantity_A	UnitCost_A	ExtendedAmount_A
000102125	STRAWGATO...	18.0	31.24	562.32
000104421	Jockamo Jul...	10.0	20.49	204.9
000100421	Purple Haze ...	99.0	20.49	2028.51
000101421	Strawberry 4...	99.0	20.49	2028.51

The screenshot displays an invoice from Abita Brewing Company, LLC, dated 3/22/2022. The interface compares three AI models: OpenAI, Gemini, and Amazon Bedrock. Each model's performance is shown as a percentage of accuracy for various fields.

Field	OpenAI	Gemini	Amazon Bedrock
VendorName_MS	100%	100%	64%
InvoiceNo_MS	100%	100%	95%
PONumber_MS	100%	100%	80%
InvoiceDate_MS	100%	100%	80%
Terms_MS	100%	100%	0%
Net 30	100%	100%	0%
SubTotal_MS	100%	100%	83%
Tax_MS	100%	100%	0%
Freight_MS	100%	100%	74%
InvoiceAmount_MS	100%	100%	87%

Models vs. Neural Templating

Performance at Scale

- ▶ Accuracy of Models vs. Templating
- ▶ **KVP mapping and parsing** hoping you programmed every permutation of a word (e.g. P.O. Number, PO #)
- ▶ **Context based**
Models don't leverage KVP's but rather uses visual context to extract data with better accuracy
- ▶ We see a **10-20% plus increase** in extraction accuracy especially with **poor quality documents and tabular data**

Neural Template

PartNumber	Description	Quantity	UnitCost	ExtendedAmount
000102125	STRAWGATO...	18.00	31.24	562.32
000104421	Jockamo Jui...	10.00	20.49	204.9
	Purple Haze ...	99.00	20.49	2028.51
	Strawberry 4...	99.00	20.49	2028.51
	Amber - 4/6/...	70.00	20.49	1434.3

LLM/Model

PartNumber_A	Description_A	Quantity_A	UnitCost_A	ExtendedAmount_A
000102125	STRAWGATOR 6/4/1...	18.0	31.24	562.32
000104421	Jockamo Juicy IPA 4...	10.0	20.49	204.9
000100421	Purple Haze 4/6/12 ...	99.0	20.49	2028.51
000101421	Strawberry 4/6/12 C...	99.0	20.49	2028.51
000100101	Amber 4/6/12 Bottles	70.0	20.49	1434.3



Chat AI within IDP

Generative AI Voting

- ▶ IDP has typically always focused on extraction and classification
- ▶ BUT when AI prompting use cases start to extend
- ▶ Ask specific questions about the current document
- ▶ Take **post extraction actions** like:
 - ▶ Summarization
 - ▶ Additional document field extraction
 - ▶ Concatenation or combining fields
 - ▶ Calculations
 - ▶ Decision criteria from previous documents

INVOICE AI

Vendor Name: Center Host Co. Vendor Address: 4762 Bourne Dr. Louisville, MS 38134 Invoice Number: 00760267

Invoice Date: 10/16/2008 PO Number: 0401-0000009992 Total: 1,038.70

Notes: 2458

I filled Notes with "2458"

Ask AI... Suggestions ▾

Next

Parsed: Center Host Co.
Extracted: Center Host Co.
Tip: Vendor Name



Gen-Classification

Generative AI Splitting

▶ AWS BDA Document Separation

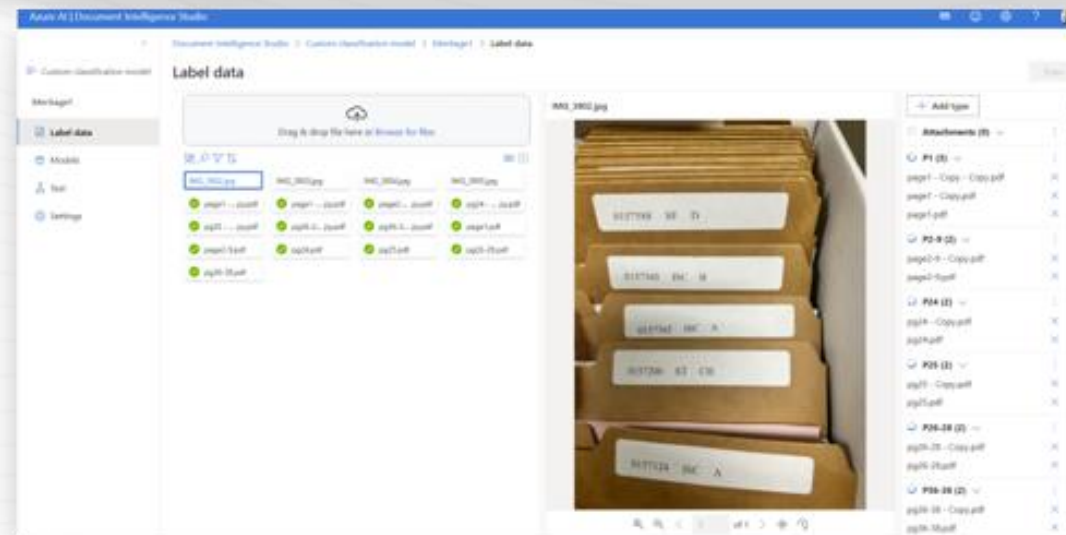
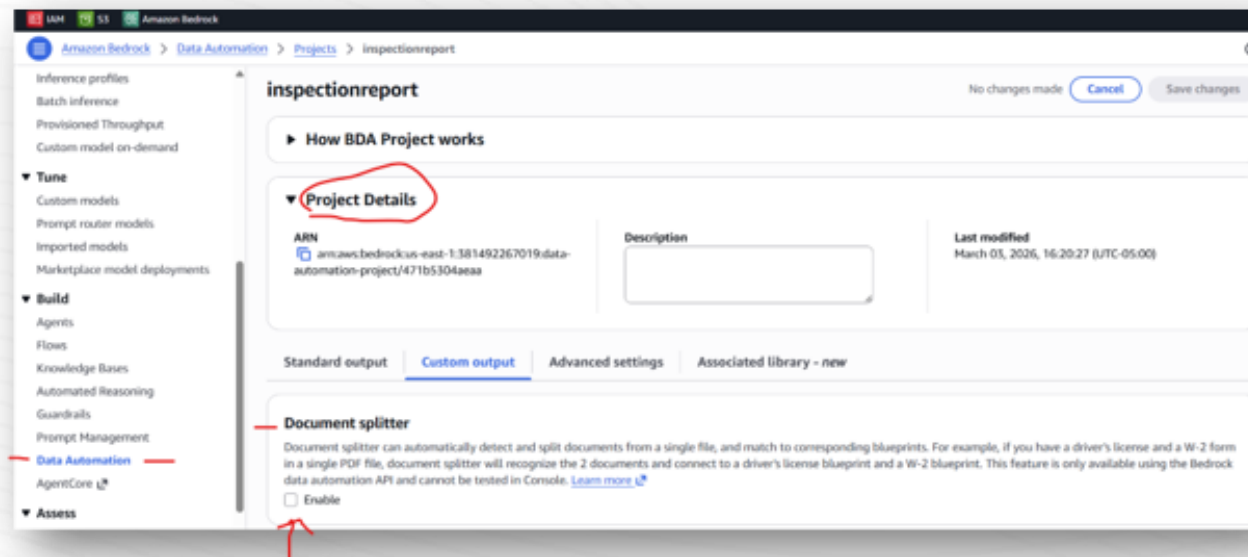
- ▶ AWS BDA Split feature
- ▶ No AWS configuration – checkbox on/off
- ▶ Enabled on the blueprint project
- ▶ Uses same AWS BDA extraction profile parameters

▶ Google DocAI

- ▶ Neural template splitting
- ▶ Only works on procurement documents
- ▶ Fails 50% of the time

▶ Azure AI Document Intelligence – Custom Classifier

- ▶ Must create a knowledgebase of types
- ▶ Not ideal for transactional documents where formats change
- ▶ Few shot learning
- ▶ Used for separation & classification



NEW ADDITIONS USE CASES



CMMC Certified Inspection Reports

▶ Customer Profile

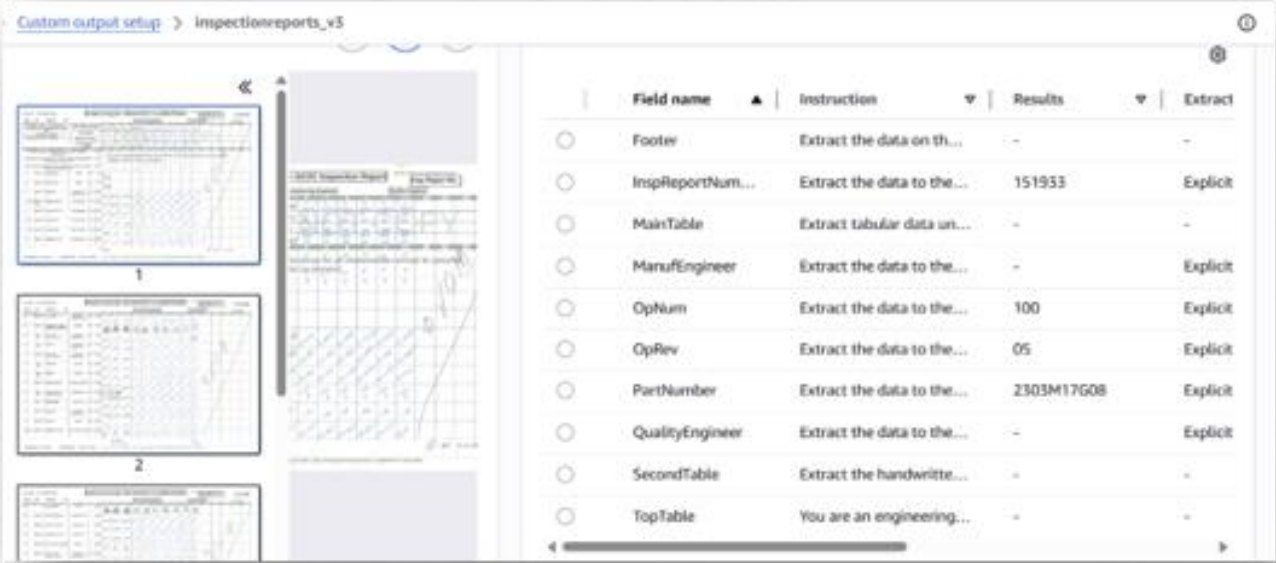
- ▶ DoD Manufacturing company that stores CMMC,CUI data in our VRC hosted DocStar ECM

▶ Use Case

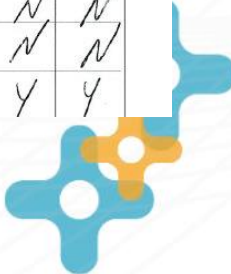
- ▶ Export out all Inspection Reports from DMS, use IDP to read and extract handwritten data from multi-page inspection reports and export to SQL Server DB for reporting/compliance

▶ Challenges

- ▶ Difficulty with misaligned tables
- ▶ Multiple disparate tables in a single document
- ▶ Tables that roll over the page
- ▶ Watermarks
- ▶ Handwriting legibility



Item #	CharNo	Dwg Loc	ZP	Drawing Requirement	Inspection Method	Class	Freq	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15				
All Dimensions listed require inspection per the specified frequency using the inspection method specified.								Shop Order/Job No.																		
Inspection Comments:								Lot Number																		
First Piece Inspection by: Operator								Machine Number																		
								Serial Number or Lot Qty																		
Item #	CharNo	Dwg Loc	ZP	Drawing Requirement	Inspection Method	Class	Freq	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15				
Indicate if this is a "First Piece Set-up" part for this operation? Indicate Y or N.								100%	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N		
Does the part have any evidence of physical damage, foreign material or contamination? Indicate Y or N.								100%	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Is/are the part(s) properly identified (i.e. Tagged, part marked, container marked, etc.)? Indicate Y or N.								100%	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y



QUESTIONS?



THANK YOU!



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