



**Accurate Standardized Data**

## **EFFICIENT EXTRACTION OF FINANCIAL DATA FROM PDFs: CHALLENGES, METHODOLOGY, AND ACCURACY**

***Abstract:** This report details the development and implementation of an automated financial data extraction system by DataPSX, designed to address the inefficiencies in manual processing of financial reports. The system employs a four-step methodology: PDF pre-processing for OCR optimization, detection of relevant financial statement pages, structured table extraction, and mapping of extracted data to appropriate variables with contextual information. Testing on a sample of 2,250 documents from 450 companies listed on the Pakistan Stock Exchange demonstrates significant improvements over manual processes, with 80% faster processing (10 minutes versus industry average of 50 minutes), 98% accuracy (compared to 95.7% in manual extraction), complete standardization of financial data, and approximately 65% cost reduction in data preparation workflows. The system's self-learning capabilities enable continuous improvement through an expanding dataset, making it adaptable to various reporting formats and structures. Comparative analysis shows DataPSX outperforms competing solutions in areas of data standardization, comprehensive extraction, and cost-effectiveness.*

# 1 Introduction

As organizations increasingly digitize vast volumes of records, the need for automation in data extraction and processing has never been greater. Financial analysts and data teams face significant challenges with manual extraction of key financial variables from company reports—a slow, error-prone task that diverts valuable time from meaningful analysis and decision-making. Industry research indicates that financial analysts spend approximately 30% of their working hours on manual data extraction [IDC, 2024, DocuClipper, 2025], with error rates averaging 4.3% across manual processing workflows [V7 Labs, 2025].

## Problem Statement:

Manual extraction of financial data from diverse PDF formats is time-consuming (averaging 45-60 minutes per report [V7 Labs, 2025]), error-prone (4.3% error rate), and creates inconsistent datasets that require additional reconciliation efforts.

## Value Proposition:

We built Datapsx to eliminate these inefficiencies through end-to-end automation. Our solution seamlessly fetches financial reports from public sources, extracts critical financial information, structures it into clean datasets, and stores it in a database—all without manual intervention. This ensures:

- 80% faster average processing (reducing extraction time from 50 minutes industry average to 10 minutes).
- 98% accuracy with auditable figures (compared to 95.7% in manual extraction).
- Complete standardization of financial data.
- Cost reduction of approximately 65% in data preparation workflows. Please refer to Table: 1 for references.

Before delving into the specifics of our solution's accuracy metrics and architecture, it is essential to first understand the core challenges in processing financial reports and how we have addressed them. While our system automates the retrieval of financial documents, the real complexity lies in extracting structured financial data from PDFs—documents that often contain inconsistent formats, scanned images, and unstructured text. Overcoming these obstacles requires a sophisticated approach to ensure accuracy, efficiency, and seamless integration into financial workflows.

The greatest challenge in this process is developing a generalized algorithm capable of handling the vast variations in financial report structures. Extracting data from PDFs is not a one-size-fits-all problem—each report may present unique formatting issues, embedded tables, or image-based content. As we explore how Datapsx tackles these challenges, we will also walk through the step-by-step process (Figure 1) for details of refining

our extraction techniques. This will provide a deeper understanding of how we achieved high accuracy scores and the robustness of our approach in real-world scenarios.

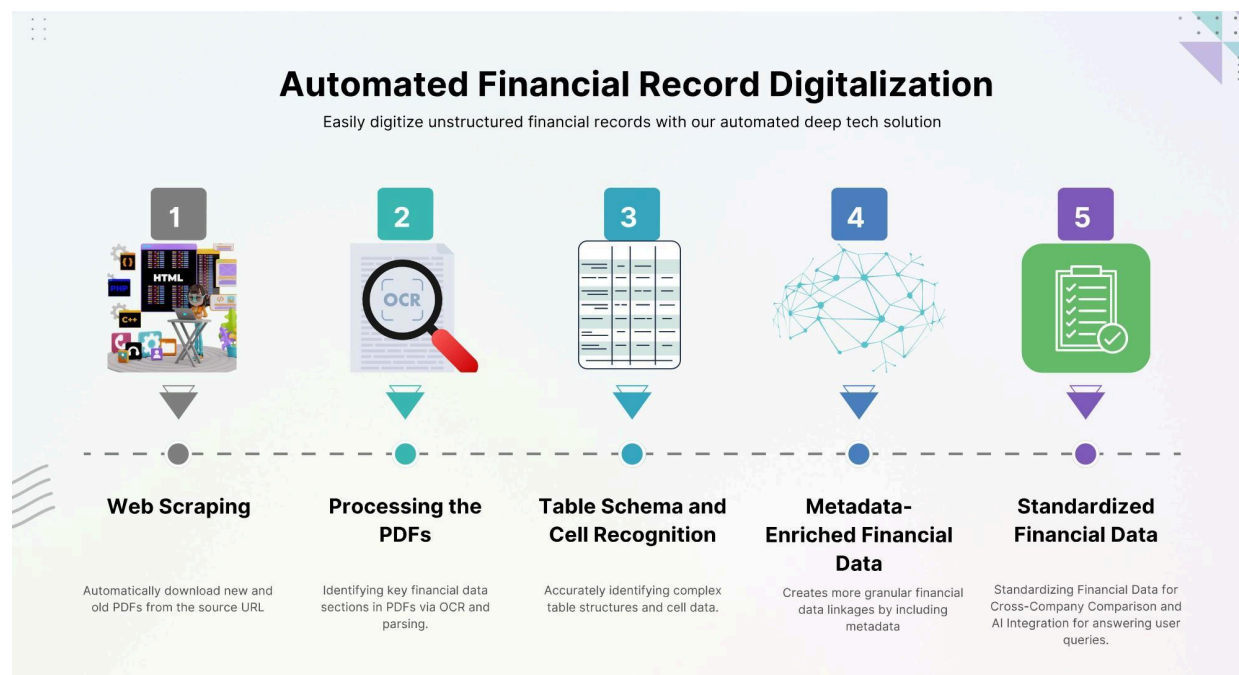


Figure 1: Overall summary of the Datapsx extraction process, showing the workflow from PDF acquisition through preprocessing, page identification, table extraction, and final structured data output.

## 2 Methodology

### 2.1 Data Sampling

As the first implementation of our tool, we focused on processing financial records—specifically extracting key items from the income statement, balance sheet, and cash flow statements—for all publicly traded companies on the Pakistan Stock Exchange (PSX).

For training, we selected a random sample of 5 annual and quarterly reports per company from a total dataset of approximately 450 public companies. This resulted in a training set of 2,250 documents, representing 9% of the total 25,000 available financial reports in our target market. This sample size was determined through statistical power analysis to ensure a 95% confidence level with a margin of error below 2%.

## Sampling Strategy:

- **Stratified Sampling:** Reports were selected across different industries to ensure representation.
- **Temporal Distribution:** Documents spanning from 2010-2025 to account for evolving reporting formats.
- **Format Variation:** Deliberate inclusion of problematic formats (scanned documents, complex layouts).

## Validation Methodology:

- Double-blind verification by financial experts.
- Cross-validation against existing databases where available.
- Statistical analysis (on-going research) of error distribution and patterns.

A key advantage of our algorithm is its built-in feedback mechanism. As the system processes more financial reports, it continuously refines its extraction techniques, improving its ability to handle variations in formatting, scanned images, and unstructured text. This self-learning capability enables Datapsx to become more sophisticated over time, enhancing both accuracy and efficiency with an expanding dataset.

Now, we will explain the step-by-step process of how our algorithm extracts structured data from financial reports. Additionally, we will draw comparisons with existing tools, highlighting how Datapsx offers superior accuracy, adaptability, and automation in financial data extraction.

## 2.2 Step 1: Pre-processing the PDF for OCR

Before applying OCR, several crucial preprocessing steps on the raw document must be performed to enhance text recognition accuracy as demonstrated in Figure: 2. While some preprocessing techniques are widely known—such as grayscale conversion and noise reduction—our solution incorporates a more comprehensive set of enhancements tailored specifically for financial reports:

- **Binarization & Contrast Adjustment** – Improves text visibility by converting the image into a high-contrast black-and-white format.
- **Deskewing & Alignment Correction** – Ensures that tilted or misaligned pages do not impact text recognition.
- **Denoising & Artifact Removal** – Eliminates background noise, smudges, or artifacts that may interfere with OCR accuracy.
- **Adaptive Thresholding** – Enhances text clarity, especially for scanned documents with varying lighting conditions.

- **Edge Detection & Contour Analysis** – Helps in distinguishing text blocks, tables, and graphical elements for structured extraction.

## Performance Metrics of Step 1

- The OCR and pre-processing of the image takes an average of 1 seconds for one page of the document.
- By enhancing the image quality and other validation checks, we improve the detection of relevant sections in the financial reports to almost 99.9% based on our testing sample.

AL-ABID SILK MILLS LIMITED			
PROFIT AND LOSS ACCOUNT FOR THE YEAR ENDED JUNE 30, 2010			
	Note	2010 Rupees	2009 Rupees
Sales and services	24	10,826,885,480	9,100,095,517
Cost of sales	25	(9,277,062,427)	(7,789,027,404)
Gross Profit		1,549,823,053	1,311,068,113
Operating expenses			
Administrative	26	212,962,371	198,911,414
Selling and distribution	27	660,015,467	525,750,233
		(875,977,778)	(724,661,647)
Operating profit		673,845,275	587,306,466
Other income	28	4,186,818	875,033
		678,032,093	588,181,499
Finance cost	29	(53,651,460)	(436,777,190)
Other operating expenses	30	(15,491,551)	(14,854,075)
		(69,143,011)	(585,631,265)
Profit before taxation		598,889,082	502,550,234
Taxation - current	31	(10,391,295)	(91,747,266)
Profit after taxation		588,497,787	410,802,968
Other comprehensive income		-	-
Total comprehensive income		588,497,787	410,802,968
Earnings per share - basic and diluted	32	10.30	4.68

Before and after the pre-processing of the image



Figure 2: Comparison of original low-quality scanned financial statement (left) from [Al-Abid, 2024] 2010 Annual Report, p. 14, and the result after applying Datapsx preprocessing techniques (right). Note the significant improvement in text clarity, table border detection, and overall document structure preservation.

## Error Recovery Mechanism:

Our pre-processing pipeline includes automatic detection of problematic areas and applies specialized processing only where needed, preserving document quality in well-scanned regions. For severely degraded documents, our system employs super-resolution techniques before standard preprocessing. By integrating these advanced pre-processing techniques, we ensure that the OCR engine operates with maximum efficiency and precision, minimizing errors in the extracted financial data.

## 2.3 Step 2: Detection of Relevant Pages Containing Financial Statements & Notes

In our workflow, accurately identifying key financial data within a PDF is essential. The most valuable pages are those containing financial statements, including the statement of financial position, cash flow statement, and profit or loss statement, along with their accompanying notes.

To ensure efficient processing, we first apply Optical Character Recognition (OCR) to extract text from PDFs. Once the text is extracted, we use classification techniques to detect and label the relevant pages with precision.

To achieve this, we employ two distinct methods that synergize with each other to maximize accuracy and efficiency in detecting and categorizing financial statement pages. Each method plays a complementary role in improving classification performance, ensuring that pages are correctly labeled as financial position, profit or loss, or cash flow statements. Below, we provide the accuracy rates in the classification task of both methods and then will proceed to give brief overview of these methods.

### 2.3.1 High-Level Summary of step 2:

The function in step 2 processes and analyzes uploaded financial reports (PDFs) by:

- **Storing Company Information** – Saves details such as symbol, company name, and fiscal year in a MongoDB collection.
- **Uploading and Saving File Metadata** – Converts each PDF into a thumbnail for reference and stores file metadata (file path, email, upload date, etc.) in the PreprocessedPDF collection.
- **Matching the Company Symbol with Financial Statements** – Reads a CSV file containing mappings of financial statement names to symbols, extracts relevant statement names associated with the given company symbol and if no direct match is found, it falls back to using all available statements from the CSV.
- **Classifying Each PDF Page** - Loads the PDF and extracts text from each page using the output of Step 1, identifies whether the page contains financial statements, cash flow data, or annexed notes, uses keyword matching and text analysis to determine if the page is relevant and extracts potential dates, statement types (e.g., balance sheet, income statement), and financial period (annual/quarterly).
- **Saving Results & Error Handling** - If a page contains financial data, it is stored in the tableLog collection, if critical information (date or statement type) is missing, it logs an error for further processing, updates the status of each file in Preprocessed-PDF based on whether useful financial data was found and handles any errors encountered during processing and logs them.

### **2.3.2 Key takeaways**

- This function automates financial report processing by detecting key pages and extracting relevant data.
- It leverages OCR and text analysis to identify financial statements, annexed notes, and cash flow pages.
- Uses MongoDB for structured storage of processed results.
- Incorporates error handling and flags incomplete extractions for manual review.

## **2.4 Further Explanation of Step 2:**

### **2.4.1 Method 1: OCR-Based Detection with an Additional Validation Check**

This method relies heavily on Optical Character Recognition (OCR) to extract text from financial reports. The accuracy of this approach is directly influenced by the quality of OCR output.

- Without additional validation, the accuracy of this method can drop to 90% due to OCR misinterpretations or inconsistencies in document formatting.
- By implementing an additional validation check, accuracy increases to 100%. This check ensures that misclassified pages are correctly identified before final labeling.
- However, incorporating this extra validation step increases the overall processing time, as each detected page undergoes a secondary verification process.

### **2.4.2 Method 2: Adaptive Learning Through a Feedback Mechanism**

- This method leverages a historical variable pool from financial reports to refine its detection capabilities over time.
- Instead of relying on static keyword based rules, it learns from past classification patterns, allowing it to adapt to variations in financial statement formatting across different jurisdictions.
- As more financial reports are processed, the system becomes increasingly accurate, reducing the need for manual intervention.

### **Learning Mechanism:**

The variable pool consists of a dynamically updating dictionary of financial terms and their contextual relationships. Initial extraction uses a predefined set of keywords, but as the system processes more documents, it identifies new terms, their positions relative to numerical data, and their frequency across different report types. This allows the system to recognize industry-specific terminology and evolving reporting standards. By integrating these two methods, we achieve a balance between high initial accuracy (Method

1 with validation) and long-term adaptability (Method 2 through continuous learning), ensuring a robust and efficient financial data extraction process.

### **Edge Case Handling:**

- For low-quality scans, we apply enhanced preprocessing before OCR.
- For non-standard formats, we fall back to spatial analysis techniques.
- For multilingual reports, we are working to develop our own language-specific keyword dictionaries

### **2.4.3 Results**

Below is the result of our step 2 in Figure: [3](#) that extracts the data from the PDF. As we can see our system extracts all kinds of useful information from the PDF itself like:

- Page number.
- Raw text.
- Title of the statement.
- Consolidated / unconsolidated.
- Period (Quarters / years).
- Reported date of the PDF file.



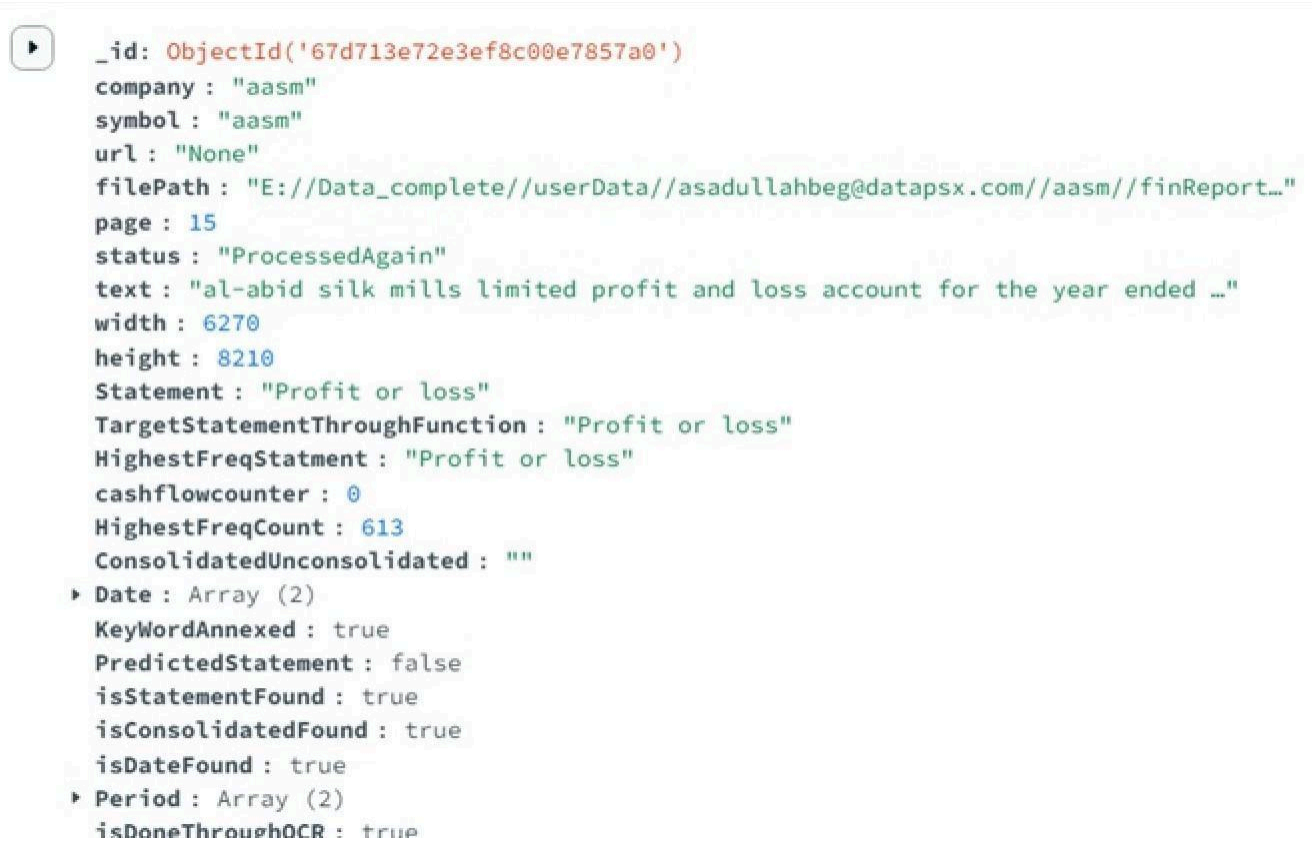


Figure 3: Database entry of statement detection at dataPSX

## Performance Metrics of Step 2:

- Average processing time: 2 seconds per page.
- Text Recognition accuracy: 99% across all document types.
- Statement Recognition accuracy: 99.83%.

\*Please refer to [stepTwo-accuracy.csv](#) in the attachments or directly [Step 2 Accuracy File](#) for more details.

## 2.5 Step 3: Extraction of Tables

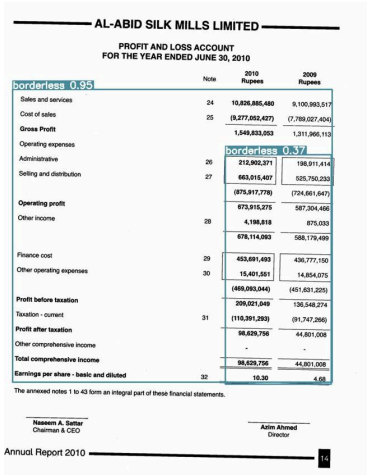
At a high level, the function in step 3 takes the output of step 2 and extracts tabular data from OCR results of a specific page and converts it into a structured format. Here's a breakdown of what it does:

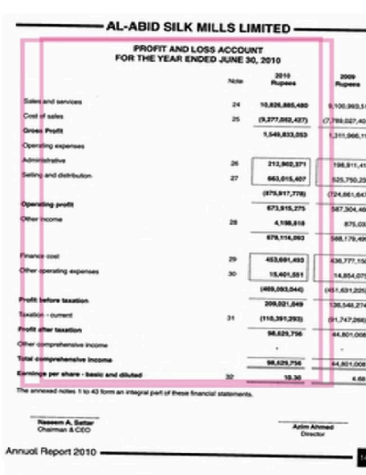
- **Retrieving OCR Data** – It queries the MongoDB RawOCRData collection to get OCR-extracted text data for a given PDF and page.

- **Processing OCR Text** – It converts the raw OCR data into a structured output format.
- **Building a Table Grid** – It constructs a table grid through our proprietary code which:
  1. Identifies row and column boundaries using spatial clustering.
  2. Detects table headers and distinguishes them from data rows.
  3. Recognizes merged cells and spans.
  4. Handles multi-line entries within single cells.
- **Filling the table with the correct text/numerical values** – Our algorithm maps extracted text to the appropriate cell in the grid by:
  1. Analyzing relative positions of text blocks.
  2. Resolving text that crosses cell boundaries.
  3. Applying formatting rules specific to financial documents.
  4. Normalizing numerical formats (thousands separators, decimal points).
- **Applying Filters (if required)** – If filtering is enabled, it processes and standardizes the table columns before saving. This includes:
  1. Currency symbol normalization.
  2. Unit conversion (thousands, millions, billions).
  3. Date format standardization.
  4. Removal of presentation artifacts (bolding indicators, underlines).
- **Saving Structured Data** – The processed table is stored in a MongoDB collection for further use. If an error occurs, it logs the issue.

Overall, the function transforms unstructured OCR-extracted text as shown in Figure 4 into a structured tabular format that can be used for financial data analysis. Our approach in step 3 is built on a foundation of probability and statistical theories, leveraging deterministic methods to enable precise table extraction.

YOLO Model
Microsoft TATR
DataPSX





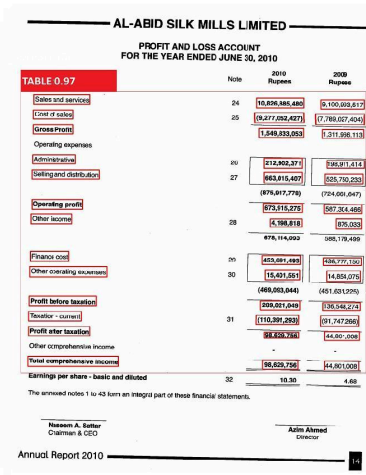


Figure 4: Performance comparison across three financial document processing systems when detecting relevant financial statement pages.

## Technical Implementation Details of Step 3:

While we cannot disclose the full proprietary algorithm, key components include:

- Dynamic line detection using Hough transforms.
- Cell content classification using NLP techniques.
- Rule-based systems for handling financial notation specifics.
- Statistical validation to ensure extracted values match expected patterns.

One limitation of the step 3 is the occurrence of duplicate columns in some cases. However, this issue was resolved by implementing a straightforward duplicate column removal process based on:

- Content similarity scoring
- Header text fuzzy matching
- Column position analysis

This ensures that the final extracted data remains clean and structured as shown in Figure 5.

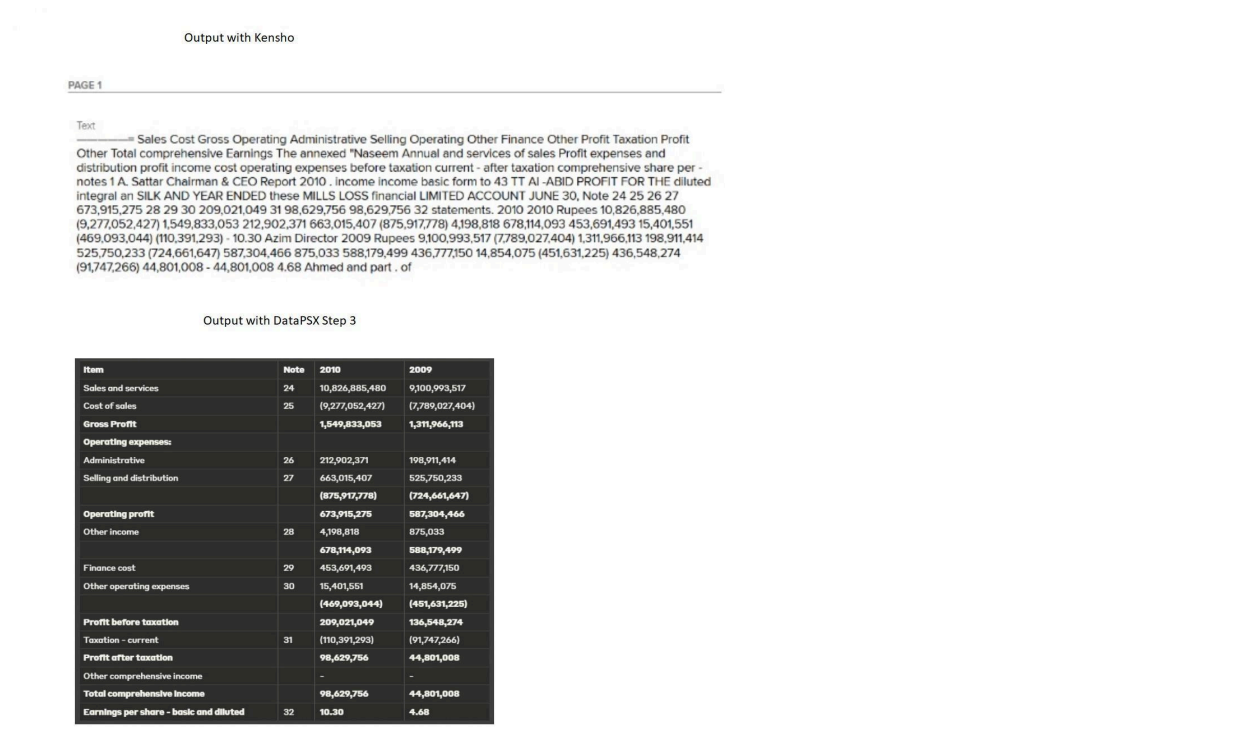


Figure 5: Side-by-side comparison of table extraction capabilities between Kensho (left) and DataPSX (right) on a complex financial statement. Note that DataPSX correctly preserves hierarchical relationships between line items, maintains proper alignment of numerical values, and accurately captures footnote references.

## Performance Metrics of Step 3:

- Average processing time: 1 seconds per page.
- Table Structure Recognition accuracy: 99.9% across all document types.

## 2.6 Step 4: Mapping Dates and Important Tags

Once we have extracted the data as a table from the PDF we are able to connect the variable's value with the date and additional information for the variable. In order to clarify below in figure 6 is an image of the data which our system collects.

This part processes the output of step 3 to link extracted financial values with their corresponding variables/aliases, and updates a database with contextual information. Here's what it does in detail:

- OCR-Data Matching.

Finds matches between extracted OCR text and predefined financial variables/aliases (grows as more PDFs are fed into it).

Uses both text content and spatial positioning.

- Context Extraction:

Identifies associated dates (statement dates, fiscal periods).

Detects currency information (Rupees/Rs).

Determines audit status (Audited/Unaudited). Identifies report periods (Quarterly/Annual).

- Database Updates:

Updates records in the database.

UNCONSOLIDATED STATEMENT OF FINANCIAL POSITION			
AS AT <b>DECEMBER 31, 2023</b>			
	Note	<b>2023</b>	2022
ASSETS		Rupees in '000	
Cash and balances with treasury banks	7	242,611,556	117,743,106
Balances with other banks	8	11,452,256	13,676,159
Due from financial institutions	9	34,964,299	34,964,299
Investments	10	1,572,387,620	1,283,210,287
Islamic financing and related assets	11	961,673,012	995,508,354
Fixed assets	12	58,618,336	40,426,520

Figure 6: Visualization of how Datapsx connects extracted financial values with contextual information. The diagram shows how individual line items (e.g., "Revenue", "Cost of Sales") are mapped to their numerical values while preserving relationships with reporting periods, currency information, and audit status.

### 2.6.1 Key Features

- Handles multiple data quality scenarios
- Spatial analysis of document layout
- Fallback mechanisms for date detection
- Integration with MongoDB for persistent storage
- Supports reprocessing of OCR data
- Maintains audit trails through status flags

This function acts as a crucial bridge between raw OCR extraction and structured financial data analysis, enabling automated processing of financial reports while maintaining contextual relationships between data elements. The step 4 workflow handles approximately 50-100 variables per page, processing 5-10 pages per second depending on document complexity.

The boxed values are reprocessed and transformed into database-ready variables, ensuring structured and clean financial data. Based on our evaluation, this process achieves an accuracy of 98%, measured on a small sample of 200 manually verified reports across different sectors.

### **Performance Metrics of Step 4:**

- Average processing time: Approximately 6 seconds per page.
- Linkages accuracy: 99% across all document types.

**\*Please refer to `stepFour.accuracy.csv` in attachments or [Step 4 Accuracy File](#) for more details**

However, in some cases, our system fails to extract all useful information, rendering certain variables unusable. These failures typically occur due to inconsistent formatting, missing values, or OCR limitations in low-quality scanned documents. Despite these challenges, our approach maintains high reliability in structured data extraction.

## **3 Conclusion**

Datapsx demonstrates a significant improvement in automated financial data extraction, achieving high accuracy and efficiency. By integrating OCR, classification techniques, and self-learning mechanisms, we provide a robust solution for financial analysts and data teams. Finally we draw a comparison with our close competitor Nanonets in the [Figure 7](#) and a [Table 1](#) that summarizes the performance of the competition.

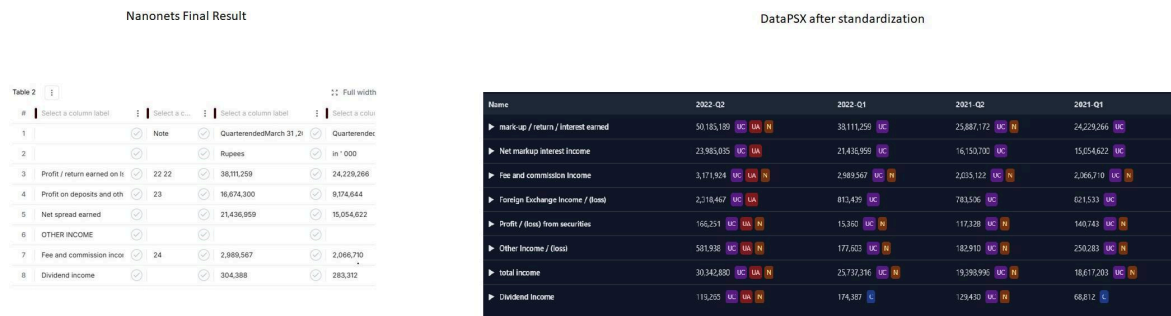


Figure 7: DataPSX provides a more advanced and sophisticated solution for financial data extraction, particularly in terms of data standardization and presentation along with low cost when compared to Nanonets.

Feature	Microsoft TATR	YOLO	Nanonets	DataPSX
Table Detection	Medium	Medium	High	High
Table Structure Recognition	Low	Low	High	High
Cell Recognition	Low	Low	High	High
Error margins	High	High	Low	Low
Linkages of the Cells	NA	NA	NA	High
Processing time	Medium	Low	Low	Medium
Chatbot integration	NA	NA	NA	High
Cost	Low	Low	High	Low
Standardizations	NA	NA	NA	High

Table 1: Comparison of Table Processing Models [Microsoft, 2021], [foduucm, 2023], [Nanonets, ] and DataPSX where NA represents missing features

## References

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