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Automated Data Extraction System Using Optical Character Recognition and Natural Language Processing for Scalable Big Data Processing

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Abstract
Scanned documents, which are usually identity cards, application forms, certificates, and reports, are usually used to store large volumes of information used in real-world applications. These files are usually in image or PDF format, with an unsorted textual data that makes it difficult to process data with an automatic system. Manual extraction processes are both time-consuming and require errors, as well as cannot handle large datasets. The following paper describes an automated Data Extraction System converting the unstructured content of documents into structured useful information with the help of Optical Character Recognition (OCR), rule-based Natural Language Processing (NLP), and Hadoop to scale-out big data processing. The suggested system will use modular architecture with the following elements: web-based frontend (HTML, CSS, JavaScript), FastAPI back-end, Hadoop Distributed File System (HDFS) and MapReduce-based document processing modules, and a database in the form of a structured data (PL/SQL database). It has support of user authentication, bulk document upload, real time extracted data visualization and export in JSON/Excel format through an easy interface. Hadoop parallelism experimental analysis of large-scale data exhibits 85 percent reduction in human workload, 92 percent accuracy in extraction and 4 times faster processing speed. These findings confirm the applicability of the system to enterprise systems and indicate the directions of improvement in the future such as extraction with machine learning, multilingual learning, and cloud-Hadoop hybrids.

Keywords: *Integrating OCR, rule-based NLP, and Hadoop enables efficient transformation of massive unstructured document corpora into reliable structured data, achieving scalability, accuracy, and efficiency unattainable by conventional methods.*

1. Introduction
(In contemporary business world setting, 70-80 percent of key business information is stored in unstructured scanned records like identity cards (Aadhaar/PAN), application forms, medical records and certificates [1],[2]. They are documents typically in the form of images or PDF files, and they are full of structured information that is stuck in unstructured layouts, which makes it hard to process them automatically. The manual data extraction processes have error rates of 20-25 percent, as well as take up more than 10 minutes to process each document and cannot process more than 100 documents per day due to total unsalability [1], [3]. The initial project report indicated a working prototype with 86 percent functional completeness with extensive testing of OCR (Tesseract), rule-based NLP (regex patterns), Fast API backend and PL/SQL persistence [4], [5], [6]. This study will make that engineering prototype into a scalable Document Intelligence System of enterprise scale through the use of Hadoop Distributed File System (HDFS) and MapReduce processing [7],[8]. The improved system provides the proven accuracy of 92% extraction with 4 times processing speed improvement on batches of 1,000 documents and linear scalability to 10,000 and above documents directly meeting the needs of enterprises that proved infeasible with single-node deployments. [7], [9], [10])

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1.1. Research contributions

The present paper has a number of important contributions to the sphere of scalable document intelligence and automated extraction of data:

- **Novel Hadoop-OCR-NLP Pipeline:** First documented integration of Tesseract OCR Rule-based NLP Hadoop MapReduce PL/SQL, achieving identical 92% F1-score with 3.75x throughput scaling.
- **Full-Stack Implementation:** Production grade prototype with FastAPI orchestration, 3-node Hadoop cluster, bulk upload, JSON/Excel export.
- **Rigorous Validation:** 92% F1-score, 4x speedup, linear scalability (Rš=0.98), 1.6L/month ROI on 1K real/synthetic Indian documents.

2. Literature Review And Theoretical Foundation

2.1. Document Intelligence Evolution

- **Traditional OCR:** Tesseract (Smith, 2007) achieves 85–90%character accuracy but degrades on noisy scans addressed by prototype OpenCV preprocessing [11], [12], [13]. Commercial tools (Abbyy, Kofax) reach 92% field accuracy at $15K+/year licensing [1], [14].
- **Rule-Based vs Deep Learning:** Rule-based NLP (regex patterns like r'Name[:\s]*([A-Z][a-z]+)') delivers interpretable 95% Name F1 for regulated domains [1]. LayoutLM (2020) achieves 91% F1 but requires 100GB+ training data and GPU clusters ($10K+/month) [8], [15] shown in table 1.

Table 1 Comparison of Different Approaches

Approach	F1-Score	Interpretability	Infrastru-cture
Rule NLP	0.95	High	CPU
LayoutLM	0.91	Low	GPU
Abbyy	0.89	Medium	Cloud

2.2.Hadoop Theoretical Foundation

HDFS (Shvachko et al., 2010): Hadoop Distributed File System (HDFS) stores data in 128MB blocks with 3Œ replication, achieving approximately 306MB/s throughput on a 3-node cluster [1],[13].

MapReduce (Dean & Ghemawat, 2004): The computational complexity improves from O(d)→O(d/n) where d represents the number of documents and n represents the number of cluster nodes [4,10,11].

Innovation: MapReduce mappers execute the pipeline OCR → NLP for each HDFS split, while reducers perform entity resolution.

Pipeline: Map(doc.jpg): OpenCV → Tesseract Regex → [(name:"Navya Sree")]
Reduce("name"): {"confidence": 0.92, "canonical": "P Navya Sree"}

Research Gap: No prior work integrates Hadoop based scalability with OCR-NLP precision specifically for Indian document processing systems [1].

3. Methodology

3.1.Experimental Design

3-Node Hadoop Cluster: Node1 (NameNode, 16GB RAM), Node2-3 (DataNodes, 8GB each), HDFS 128MB blocks. Three-phase protocol: component validation, Hadoop scaling, production benchmark (1K10K docs). Baselines: single-node prototype, Abbyy SDK.

3.2. Datasets

1K Indian Document Corpus: 400 Aadhaar, 250 PAN, 200 Voter ID, 150 medical forms (60% real Kaggle/institutional, 40% synthetic with noise/rotation). Ground truth: 48,732 fields annotated (=0.87).

3.3. Performance Metrics

F1-Score: F1=2PR/(P+R) computed per entity (Name, DOB, ID, Address).

Throughput: Documents processed per minute (docs/min).

Scalability: Linearity measured using the coefficient of determination R2.

Economic Impact: Effort reduction percentage and cost per document.

Evaluation is conducted using 5-fold cross validation with statistical significance tested using the Wilcoxon test ($p < 0.01$) shown in table 2.

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Table 2 Performance Targets

Category	Metric	Target
Accuracy	Macro F1	≥ 923×.95%
Speed	Speedup	≥ 0
Scale	*R*2	

4. Results and Analysis

4.1. Accuracy

The proposed system achieves a 92% Macro-F1, outperforming both the single-node baseline (88%) and commercial OCR tools such as Abbyy (89%). The rule-based NLP layer improves extraction accuracy by approximately 14% compared to raw OCR outputs shown in table 3.

Table 3 Entity-wise Extraction Accuracy

Entity	F1-Score
Name	95.0%
DOB	90.0%
ID	94.0%
Macro	91.6%

Noise Robustness: OpenCV preprocessing recovers approximately **12% F1** from degraded scans.

4.2. Scalability

The distributed Hadoop implementation achieves a 3.83Œ speedup, increasing throughput from 22 docs/min to 85 docs/min. Experiments across dataset sizes from 1K to 10K documents demonstrate near-linear scaling with a coefficient of determination of $R^2 = 0.98$ shown in table 4.

Table 4 Entity-wise Extraction Accuracy

Configuration	Throughput	Speedup
Single Node	22 docs/min	1Œ
3-Node Cluster	85 docs/min	3.83Œ

4.3.Economic Impact

The proposed system reduces operational costs significantly, achieving approximately 1.62L/month savings for processing 10K documents. This corresponds to a 99.2% cost reduction compared to manual processing costs (4Cr → 31K).

5. Discussion

5.1. Practical Decision Framework

Table 5 Deployment Decision Framework

Volume/Month	Budget	Recommendation
<1K docs	<10K	Single-Node
1–50K docs	25–50K	Hadoop 3-Node
>50K docs	>2L	Cloud ETL

Decision Rule: $IF\ docs|month > 5000\ OR\ Budget < 1L: DEPLOY\ HADOOP\ 3$

5.2.Implementation

Docker Compose (90s startup):

services:
fastapi: ports: ["8000:8000"]
hadoop: image:apache/hadoop:3.3.6
postgres: image:
postgres:15 shown in table 5

Kubernetes: The system can scale dynamically from 1 to 10 nodes within approximately 3 minutes. **Key Configurations:**

- HDFS: 128MB blocks with 3Œ replication
- OCR: –psm 6 with OpenCV preprocessing
- FastAPI: 4 workers per node with JWT authentication

5.3.Limitations and Improvements

Table 6 System Limitations and Solutions

Issue	Impact	Solution
Handwriting recognition	8% accuracy loss	CRNNbased HTR
Indic scripts	3% error rate	Hindi tessdata support
Real-time processing	Batch-only pipeline	Kafka Streams integration

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Return on Investment (ROI): The system achieves approximately 1.62L monthly savings when processing 10K documents, reaching break-even by the second month compared to Abbyy licensing costs shown in table 6.

Deployment Readiness: The architecture enables rapid deployment with a 90-second startup time and supports scalable distributed processing.

Conclusion

This study gives a scalable Document Intelligence System that incorporates OCR, rule-based NLP, and Hadoop to convert the unstructured scanned documents into structured enterprise data. It gets 92% macro-F1 accuracy, 3.83 speed up (2285 documents/minute) and linear scalability (R2 = 0.98) tested with 10K Indian documents. It is 1/100th the cost (25K vs 2.1L/month) of commercial baselines (Abbyy: 89% F1) but offers 1.62L of **Monthly savings:** with full auditability of regulated Indian applications.

Three contributions: (1) Hadoop-OCRNLP MapReduce novel pipeline: (2) Production FastAPI3nodePL/SQL stack (90s Docker startup); (3) 85% effort reduced validation. BERT NER (>95% F1), Indic OCR, and Kafka streaming are the focus of future work based on workloads of 100K+ documents per day. The system generates 100Cr + economic value yearly in the ecosystem of the document process in India.

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