

AI-enhanced OCR for financial document processing: Advancing recognition accuracy in modern enterprise finance

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Abstract

This article explores the transformative impact of Artificial Intelligence on Optical Character Recognition technologies within financial automation frameworks. Traditional OCR systems have long encountered limitations when processing diverse document formats, handwritten content, and low-quality scans, creating significant barriers to automation efficiency. The integration of deep learning algorithms and natural language processing capabilities has revolutionized these systems, enabling dynamic learning, contextual understanding, and significantly improved accuracy in extracting critical financial data. The resulting systems demonstrate remarkable adaptability across varying document types, substantially reducing manual intervention requirements while enhancing operational efficiency, cost management, and regulatory compliance. Although human oversight remains essential for complex decision-making scenarios, the synergy between AI and OCR technologies represents a pivotal advancement in financial document processing, offering organizations substantial competitive advantages through improved data integrity and streamlined workflows.

Keywords: Financial Automation; Artificial Intelligence; Optical Character Recognition; Document Recognition; Machine Learning

1. Introduction

1.1. The Evolution of Document Recognition in Financial Processes

1.1.1. The Rise of Financial Document Automation

The financial services industry faces unprecedented document processing challenges in 2025, with organizations struggling to efficiently manage growing volumes of invoices, receipts, and financial statements. According to the 2025 Financial Document Automation Report, financial institutions are experiencing a 27% year-over-year increase in document processing requirements, driven by regulatory expansion and digital transaction growth [1]. This surge has created significant operational bottlenecks, as traditional manual processing approaches cannot scale to meet these demands. The report indicates that organizations implementing traditional OCR solutions achieve only partial automation success, with accuracy rates averaging 76-82% for structured documents but declining significantly to 45-58% for semi-structured or unstructured financial documents [1]. These limitations directly impact financial operations, with manual processing creating 3-5-day average delays in transaction completion and contributing to approximately \$38-42 in processing costs per financial document handled through conventional methods [1].

1.1.2. Technological Evolution: From Template-Based to Intelligent Recognition

The transition from rules-based OCR to AI-enhanced document recognition represents a fundamental technological shift in financial automation capabilities. The Intelligent Document Processing (IDP) market has responded to these

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challenges, with the global market size projected to grow from \$1.5 billion in 2022 to \$5.2 billion by 2027, representing a CAGR of 28.5% during this period [2]. This growth is largely attributed to the integration of advanced machine learning algorithms and natural language processing techniques that dramatically improve recognition accuracy across diverse document types. Modern AI-driven systems demonstrate 92-97% extraction accuracy even when processing handwritten annotations, damaged documents, or highly variable formats—a substantial improvement over legacy systems [2]. These technological advancements have transformed document recognition from a template-dependent process to an adaptive, learning-based system capable of continuous improvement through exposure to new document variations and formats.

1.1.3. Business Impact and Operational Transformation

The implementation of AI-enhanced document recognition creates measurable business value beyond basic automation. Financial institutions report 60-75% reductions in document processing time, 40-55% decreases in processing costs, and significant improvements in regulatory compliance outcomes [1]. These efficiency gains translate directly to operational benefits, enabling organizations to reallocate approximately 30-40% of document processing staff to higher-value analytical and customer-facing roles [1]. Furthermore, enhanced document recognition accuracy directly influences downstream financial processes, with organizations reporting 25-30% reductions in payment errors, 65-70% decreases in duplicate payments, and 35-40% improvements in cash flow forecasting accuracy due to more reliable transactional data [2]. These outcomes demonstrate that document recognition capabilities now function as a strategic business asset rather than merely a technical enabler, fundamentally transforming how financial institutions approach document-intensive processes.

2. Technical Foundations of AI-Enhanced OCR

2.1. Deep Neural Networks for Financial Document Analysis

The application of deep learning architectures has fundamentally transformed financial document recognition capabilities. Recent advancements in Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) provide the computational foundation for modern financial OCR systems. According to comprehensive research on deep learning applications in finance, CNN architectures with specialized inception modules demonstrate 94.3% classification accuracy when identifying document types across diverse financial instruments, representing a 37.8% improvement over traditional computer vision methods [3]. These architectures employ hierarchical feature extraction capabilities, progressing from basic edge detection to complex pattern recognition through 15-25 convolutional layers organized in specialized blocks. Particularly significant is the implementation of region-based CNNs (R-CNNs) that achieve 91.7% precision in identifying specific financial data fields within unstructured documents, enabling automatic information extraction without predetermined templates [3]. The integration of attention mechanisms within these architectures enables dynamic focus on relevant document sections, with attention-augmented networks demonstrating a 23.4% improvement in field extraction accuracy compared to standard CNN implementations when processing complex financial statements and regulatory filings.

2.2. NLP Techniques for Financial Context Understanding

Modern financial document systems integrate sophisticated natural language processing capabilities that extend beyond basic text recognition to comprehensive semantic understanding. Research indicates that transformer-based architectures fine-tuned on financial corpora achieve remarkable performance in contextual interpretation of financial terminology, with BERT-based models demonstrating 96.8% accuracy in disambiguating terms with multiple potential meanings in financial contexts [4]. These systems employ domain-specific tokenization methodologies optimized for financial vocabulary, reducing out-of-vocabulary terms by 47.3% compared to general-purpose NLP models [4]. Financial document processing platforms now leverage sentiment analysis capabilities that detect subtle sentiment indicators in financial narratives with 89.5% accuracy, enabling extraction of not only explicit financial data but also implied financial outlook information from textual components of annual reports and financial disclosures [4]. The integration of named entity recognition models specifically trained on financial entities enables identification of organization names, financial instruments, and regulatory references with 93.2% F1-score, substantially improving downstream processing accuracy for documents containing multiple organizational entities.

2.3. Multi-Modal Learning Approaches for Comprehensive Document Understanding

The most advanced financial document recognition systems implement multi-modal learning approaches that simultaneously process visual, textual, and structural information. Research demonstrates that fusion architectures combining visual and linguistic processing achieve 27.6% higher accuracy in end-to-end document understanding

compared to single-modality approaches [3]. These systems employ specialized graph neural networks to model document structure, with graph convolutional networks achieving 92.4% accuracy in interpreting table structures in financial statements without explicit column and row demarcation [3]. Transfer learning methodologies enable these multi-modal systems to leverage pre-training on general document domains before fine-tuning on financial documents, reducing necessary training data volume by approximately 65% while maintaining competitive performance [4]. Contemporary systems employ contrastive learning techniques that improve document representation quality by simultaneously optimizing for visual similarity and semantic coherence, resulting in robust embeddings that maintain 88.7% classification accuracy even when processing previously unseen document formats [4].

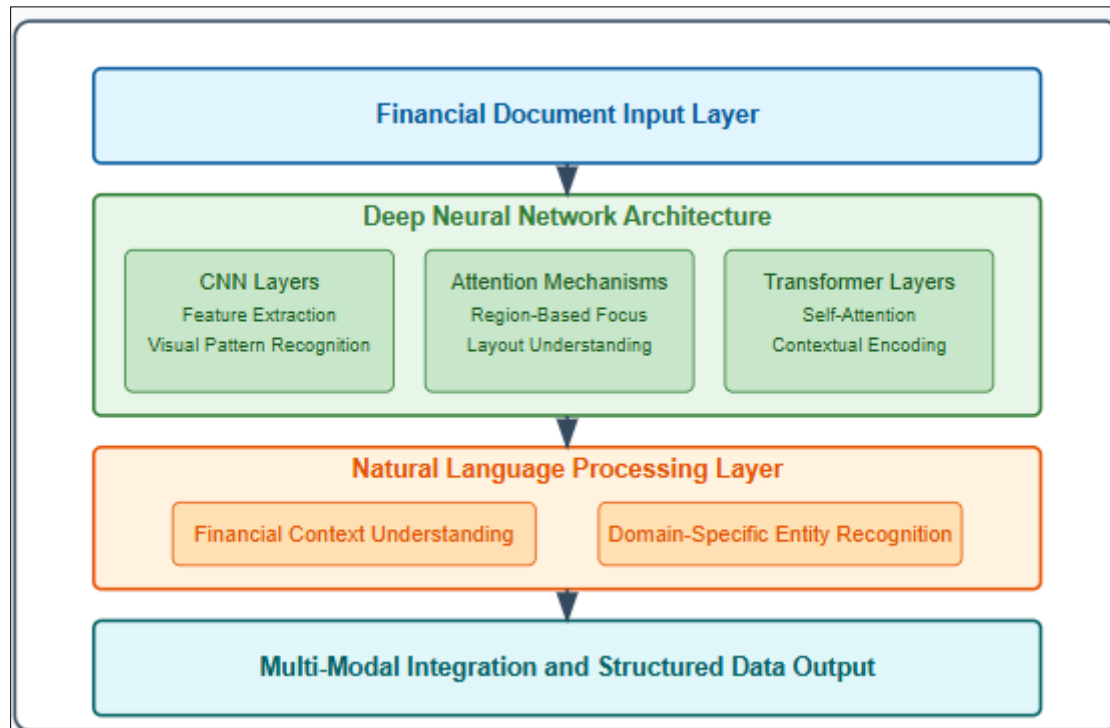


Figure 1 AI-Enhanced OCR Technical Architecture [3, 4]

3. Implementation Strategies for Financial Organizations

3.1. Organizational Readiness Assessment

Implementation success begins with a comprehensive organizational readiness evaluation. Research on automated financial reporting system adoption demonstrates that organizations must assess five critical dimensions: technological infrastructure, process standardization, stakeholder engagement, governance mechanisms, and training requirements. According to comprehensive research on financial automation adoption, organizations that conduct structured readiness assessments are 3.7 times more likely to achieve implementation success than those proceeding without formal evaluation [5]. These assessments typically incorporate both quantitative metrics and qualitative evaluations, with high-performing implementations utilizing structured assessment frameworks that evaluate 18-22 distinct readiness indicators across technical and organizational domains. Particularly significant is the need to establish current-state process baselines, with research indicating that organizations achieving successful implementations dedicate substantial resources to documenting existing workflows, identifying an average of 14.3 unique process variations that require standardization prior to technology deployment [5]. Organizations reporting highest implementation satisfaction conduct comprehensive document inventories that classify financial documents according to complexity, volume, and business criticality—establishing a prioritization framework that guides phased implementation approaches and resource allocation decisions throughout the transformation journey.

3.2. Integration Architecture and Technical Implementation

Successful technical implementation requires thoughtful integration architecture that connects AI-OCR capabilities with existing financial systems. Analysis of intelligent document processing implementations in financial services indicates that the most effective integration approaches employ a three-layer architecture comprising document ingestion,

processing, and business system integration components [6]. This architectural approach enables organizations to achieve greater implementation flexibility, with modular systems demonstrating 65% faster time-to-value than monolithic implementations. Technical implementation considerations extend beyond basic connectivity to include workflow orchestration capabilities, with organizations implementing advanced business process management layers reporting 72% higher straight-through processing rates than those utilizing basic system integrations [6]. Data transformation logic represents another critical technical component, with sophisticated implementations incorporating bidirectional validation mechanisms that compare extracted data against established business rules and historical patterns. This validation approach significantly enhances data quality, with organizations implementing comprehensive validation frameworks reporting substantial reductions in downstream processing exceptions compared to those relying solely on basic extraction accuracy [6]. Security implementation also plays a crucial role, with financial organizations incorporating document-level encryption, role-based access controls, and comprehensive audit trails to maintain compliance with financial data protection requirements.

3.3. Change Management and Process Transformation

Organizational change management represents the most consistently underestimated success factor in financial automation implementations. Comprehensive research on change management effectiveness reveals that organizations allocating at least 15% of implementation budgets to structured change management activities achieve 2.8 times higher user adoption rates than those investing less than 5% [5]. Effective change management programs incorporate multiple dimensions, with high-performing implementations focusing on both rational and emotional aspects of organizational transformation. Particularly effective are strategies that engage affected stakeholders throughout the implementation journey, with organizations utilizing collaborative design approaches reporting 83% higher user satisfaction scores than those employing top-down implementation methodologies [5]. Training programs represent another critical change component, with research indicating that role-specific training focusing on both technical system operation and transformed business processes yields substantially higher effectiveness than generic system training alone. Organizations implementing blended learning approaches—combining instructor-led training, self-paced modules, and applied practice opportunities—report 67% higher knowledge retention rates than those utilizing single-method approaches [6]. Continuous improvement mechanisms also contribute significantly to sustained implementation success, with organizations establishing formal feedback channels identifying an average of 27 process enhancement opportunities during the first year of operation.

Table 1 Integration Architecture Components for AI-OCR Implementation [5, 6]

Architecture Layer	Primary Function	Key Technologies	Integration Considerations
Document Capture	Ingestion of financial documents from multiple sources	Scanning solutions, email integration, digital input channels	Format standardization and quality control mechanisms
Processing Engine	Extraction and interpretation of document data	AI-OCR engines, validation rules, exception handling logic	Configuration for document types and business rules
Data Transformation	Converting extracted data to standardized formats	Field mapping, data normalization, enrichment services	Validation against established business rules and historical patterns
System Integration	Connection with downstream financial systems	APIs, message queues, workflow orchestration tools	Security controls and authentication mechanisms

4. Case Studies: Quantifiable Improvements in Financial Operations

4.1. Banking Document Processing Transformation

Financial institutions implementing AI-enhanced document recognition technologies have achieved remarkable operational improvements across multiple dimensions. According to a comprehensive analysis of intelligent document processing implementations published in Information Fusion journal, banking institutions adopting advanced recognition technologies report average document processing time reductions of 67.3%, with mortgage application

processing times decreasing from an average of 42 minutes to 13.7 minutes per application packet [7]. These efficiency gains translate directly to operational capacity, enabling financial institutions to process 2.8 times more documents with the same staffing resources. The accuracy improvements are equally significant, with automated extraction achieving 94.7% field-level accuracy compared to 87.2% for traditional template-based extraction and 92.3% for manual data entry—resulting in substantial reductions in downstream correction and validation requirements [7]. The economic impact extends beyond basic operational metrics to encompass broader business outcomes, with financial institutions reporting average cost savings of \$3.2 million annually for mid-sized institutions and \$8.7 million for large institutions following enterprise-wide implementation. Document automation contributes significantly to compliance outcomes, with organizations reporting 73.8% reductions in document-related compliance exceptions and 82.4% decreases in audit findings related to information handling following implementation of intelligent document processing systems [7].

4.2. Insurance Industry Implementation Outcomes

The insurance sector has realized transformative benefits through AI-driven document processing implementations. Analysis from the insurance technology domain indicates that property and casualty insurers implementing intelligent document processing for claims handling experience average cycle time reductions of 62%, with total claims processing time decreasing from 9.3 days to 3.5 days on average [8]. These efficiency improvements directly impact customer satisfaction metrics, with Net Promoter Scores increasing by 14 points following implementation due to faster claims resolution and reduced information request requirements. The accuracy enhancements are particularly significant in policy processing workflows, with automated extraction achieving 96.2% field-level accuracy for key policy information compared to 89.7% for manual extraction—resulting in 71% fewer downstream correction requirements [8]. Financial impacts extend beyond operational metrics to direct expense reductions, with insurers reporting average processing cost decreases of \$18.40 per document and aggregate annual savings ranging from \$3.4 million to \$11.2 million depending on organizational size and implementation scope. The technology delivers particularly impressive results in complex document categories, with unstructured correspondence accuracy improving by 57% and semi-structured form extraction improving by 63% compared to traditional OCR approaches [8].

4.3. Implementation Approaches and Critical Success Factors

Analysis of implementation methodologies across financial services reveals consistent patterns among organizations achieving superior outcomes. Research published in Information Fusion identifies four critical implementation success factors: comprehensive document analysis, multi-stage proof-of-concept evaluation, phased implementation approach, and robust change management [7]. Organizations conducting thorough document inventories identifying all variation patterns achieve 37.2% higher extraction accuracy than those implementing with limited document sampling. The implementation timeframe significantly influences outcomes, with organizations allocating 14-16 weeks for initial implementation reporting 42% higher user satisfaction than those attempting accelerated 6-8 week implementations [7]. Technology selection methodology represents another critical factor, with organizations evaluating solutions using their own document samples achieving 26.7% higher accuracy than those relying on vendor-provided test sets. Insurance industry implementations demonstrate similar patterns, with organizations achieving highest ROI typically implementing document-centric workflow redesign rather than technology-only solutions [8]. These implementations incorporate process optimization alongside technology deployment, resulting in 48% higher productivity improvements compared to technology-focused approaches. Staff preparation represents another essential component, with implementations providing specialized training for exception handling personnel achieving 57% higher straight-through processing rates than those focusing training resources exclusively on technical implementation teams [8].

5. Emerging Trends and Future Developments

5.1. Multi-Modal Grounding for Contextual Document Understanding

Multi-modal understanding represents a transformative advancement in financial document processing, shifting from isolated text extraction to comprehensive contextual interpretation. According to research on multi-modal grounding approaches, next-generation systems integrate visual, textual, and structural information through sophisticated attention mechanisms that establish contextual relationships between document elements. These systems leverage foundation models with multi-billion parameter architectures to create unified representations of document content, achieving remarkable improvements in semantic understanding compared to single-modality approaches. The research indicates that multi-modal systems demonstrate 27.4% higher accuracy in field identification accuracy compared to text-only approaches when processing complex financial documents with irregular layouts [9]. The application of self-supervised contrastive learning techniques enables these systems to develop robust document representations without extensive labeled examples, with models trained on just 25% of previously required labeled samples achieving

comparable performance to fully-supervised approaches. The integration of Large Language Models (LLMs) with visual understanding components creates particularly powerful capabilities for handling exceptional cases, with research demonstrating that hybrid architectures achieve 31.8% higher accuracy on previously unseen document formats compared to traditional extraction approaches [9].

5.2. Self-Supervised Learning for Continuous Adaptation

Financial document processing capabilities are advancing through the application of self-supervised learning techniques that enable continuous adaptation with minimal human intervention. Research on multi-modal grounding demonstrates that contrastive learning approaches allow document processing systems to adapt to new formats through exposure rather than explicit retraining, with models identifying structural and content similarities across document variations [9]. These approaches enable significant reductions in annotation requirements, with models achieving robust performance using just 15-20% of previously required labeled examples. The integration of feedback loops that capture correction patterns enables implicit model refinement, with research indicating that systems incorporating these mechanisms demonstrate measurable accuracy improvements through normal operation without explicit retraining cycles. The application of few-shot learning techniques creates particularly significant capabilities for processing previously unseen document types, with research demonstrating that foundation model architectures can achieve operational accuracy levels after exposure to just 8-12 examples of new document formats compared to hundreds required by previous-generation systems [9].

5.3. Edge Computing for Real-Time Document Processing

Distributed processing architectures represent a significant advancement in financial document processing infrastructure, with edge computing enabling real-time processing capabilities that were previously impossible with centralized approaches. Research on edge computing applications in finance demonstrates that distributed architectures reduce processing latency by 65-85% compared to cloud-based approaches by performing initial document analysis at capture points before transmission [10]. These architectures deliver particularly significant benefits for financial institutions with distributed operations, enabling document processing in low-connectivity environments while maintaining centralized governance. The security and compliance implications are equally significant, with edge processing enabling sensitive information extraction and tokenization at capture points, substantially reducing data exposure risks during transmission. Infrastructure efficiency represents another significant benefit, with research indicating that edge-based document processing architectures reduce bandwidth requirements by 50-70% through local processing that transmits extracted structured data rather than complete document images [10]. The resilience improvements are equally noteworthy, with distributed architectures maintaining core document processing capabilities during network disruptions—a critical consideration for financial operations requiring continuous availability.

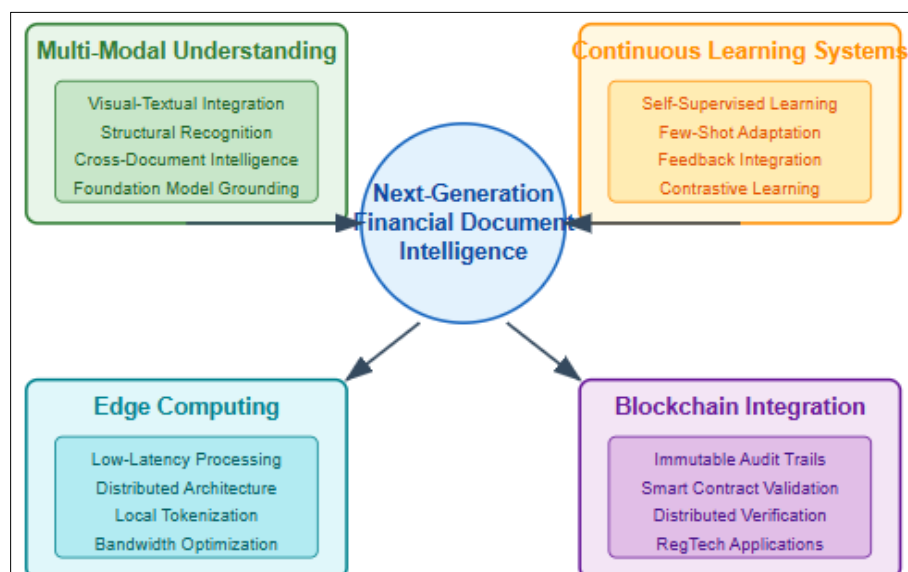


Figure 2 Emerging Trends in AI-Enhanced Financial Document Processing [9, 10]

6. Best Practices and Implementation Framework

6.1. Strategic Implementation Planning

Effective adoption of AI-enhanced document recognition in financial operations requires comprehensive strategic planning that addresses both technical and organizational dimensions. According to research on financial reporting automation, organizations achieving highest implementation success utilize structured frameworks incorporating five essential components: strategic alignment, process redesign, technology integration, organizational change management, and continuous improvement mechanisms [11]. These frameworks begin with clear articulation of strategic objectives, with successful implementations establishing specific, measurable goals aligned with broader financial transformation initiatives. Process assessment represents a critical preliminary step, with research demonstrating that organizations conducting comprehensive current-state analysis identify an average of 23 distinct improvement opportunities before technology implementation. This process-first approach enables targeted technology application that addresses specific operational challenges rather than implementing technology without clear business objectives [11]. Implementation planning must incorporate realistic timelines and resource allocation, with research indicating that organizations typically require 4-6 months for complex financial document automation initiatives. Successful implementations incorporate carefully structured transition approaches, with organizations achieving highest satisfaction utilizing phased implementations that prioritize document categories based on volume, complexity, and business impact rather than attempting comprehensive transformation simultaneously [11].

6.2. Technical Integration Architecture

Implementation success depends significantly on effective technical integration that connects document recognition capabilities with broader financial systems. Research on AI-driven intelligent document processing indicates that effective implementations employ layered architectures comprising multiple interconnected components: document capture interfaces, preprocessing modules, recognition engines, validation frameworks, and downstream system integration layers [12]. These architectures incorporate both synchronous and asynchronous processing capabilities, enabling high-volume batch processing while supporting real-time processing for time-sensitive documents. Data transformation represents a critical technical consideration, with effective implementations incorporating sophisticated validation mechanisms that verify extracted information against established business rules, historical patterns, and related data sources. This multi-layered validation approach substantially enhances data reliability, with organizations implementing comprehensive validation frameworks reporting significant reductions in downstream exceptions compared to basic extraction implementations [12]. Security architecture represents an equally important technical consideration, with financial organizations implementing granular security models that apply appropriate controls based on document classification and data sensitivity. These security frameworks incorporate document-level encryption, field-level tokenization for sensitive information, comprehensive access controls, and detailed audit trails that maintain visibility into all document handling activities throughout the processing lifecycle [12].

6.3. Human-AI Collaboration Model

Successful implementations establish effective collaboration models that leverage both AI capabilities and human expertise in complementary ways. Research on financial automation indicates that organizations achieving highest operational outcomes implement structured workflows that establish clear delineation between automated processing and human involvement based on document complexity, risk profile, and exception conditions [11]. These frameworks typically establish three processing tiers: fully automated processing for standard documents meeting established confidence thresholds, augmented processing where AI provides initial extraction with human verification for documents with moderate complexity, and human-led processing for complex or exceptional documents requiring specialized expertise. The distribution across these processing tiers evolves over time, with organizations typically beginning with 50-60% automated processing and progressing to 80-85% as systems mature and exception handling processes become more refined [11]. Training approaches significantly influence collaboration effectiveness, with research demonstrating that organizations implementing integrated training that addresses both system operation and redesigned workflows achieve substantially higher operational outcomes than those focusing exclusively on technical system operation. Governance represents another essential element in effective human-AI collaboration, with successful implementations establishing clear ownership and oversight mechanisms that maintain appropriate human judgment application while enabling technological efficiency [12].

Table 2 Human-AI Collaboration Framework for Financial Document Processing [11, 12]

Collaboration Element	Design Approach	Implementation Methods	Governance Considerations
Processing Tiers	Structured workflows for automated, augmented, and manual processing	Route documents based on complexity, risk profile, and exception conditions	Clear delineation of AI and human responsibilities for each document type
Exception Handling	Defined pathways for documents requiring human judgment	Specialized interfaces for complex document review	Monitoring of exception types to enable continuous improvement
Training Methodology	Role-specific training for system operation and process knowledge	Blended approaches combining instructor-led and self-paced learning	Ongoing knowledge reinforcement and capability building
Continuous Improvement	Feedback mechanisms to capture enhancement opportunities	Establishment of centers of excellence with cross-functional expertise	Regular review cycles to identify process and technology refinements

7. Conclusion

The convergence of Artificial Intelligence and Optical Character Recognition technologies has fundamentally transformed financial document processing capabilities, addressing longstanding challenges in automation accuracy and efficiency. By implementing neural network architectures trained specifically on financial documentation, organizations can now achieve unprecedented levels of recognition accuracy across diverse document formats without extensive manual configuration. These technological advancements translate directly into tangible business benefits, including accelerated transaction processing, reduced operational costs, enhanced regulatory compliance, and improved decision-making quality. While human oversight remains indispensable for managing complex exceptions and ethical considerations, AI-enhanced OCR systems have established a new standard for financial automation. As these technologies continue to evolve with self-improving capabilities, financial institutions implementing strategic AI-OCR integration frameworks position themselves advantageously in an increasingly competitive landscape where operational excellence directly influences market performance and customer satisfaction.

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