AI-Driven Document Intelligence based Supply Chain Automation Using Invoice Processing and Intelligent Querying

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***Abstract*—The rapid digitization of supply chain operations has intensified the need for intelligent systems capable of processing large volumes of semi-structured and unstructured documents such as invoices. Traditional methods relying on manual data entry or Optical Character Recognition (OCR) systems suffer from limitations in scalability, accuracy, and contextual understanding. This research presents an AI-driven document intelligence system designed to automate invoice processing and enable intelligent querying through a Retrieval-Augmented Generation (RAG) framework. The system integrates Vision-Language Models (VLMs), semantic embeddings, anomaly detection mechanisms, and knowledge distillation techniques to achieve both high performance and deployment efficiency.**

A modular pipeline architecture is employed, consisting of an ingestion pipeline for document processing and a query pipeline for semantic retrieval and response generation. The ingestion pipeline performs preprocessing, hybrid extraction, structuring, validation, and embedding generation, while the query pipeline leverages vector similarity search and large language models to provide context-aware responses. Furthermore, knowledge distillation is applied to compress large language models into smaller, efficient student models, enabling faster inference and reduced computational cost without significant loss in performance.

Experimental evaluation demonstrates that the proposed system significantly outperforms traditional OCR-based approaches in terms of contextual understanding, flexibility across document formats, and query capabilities. The system achieves high accuracy in structured data extraction while maintaining scalability and usability for non-technical users. This work highlights the potential of combining document intelligence, semantic retrieval, and model compression to build practical, real-world AI systems for supply chain automation.

I. INTRODUCTION

Supply chain systems depend heavily on document-centric workflows. Invoices, purchase orders, receipts, delivery notes, and transport bills serve as primary transactional artifacts for inventory updates, payment verification, supplier reconciliation, and auditing. In practical industrial environments, these documents are generated by multiple vendors using different layouts, formatting conventions, scanning qualities, and sometimes handwritten annotations. As a result, the information required for downstream automation is often embedded in semi-structured or unstructured visual documents rather than directly available in machine-readable form. This creates a major bottleneck in operational efficiency.

Despite the digitization of enterprise systems, invoice processing in many organizations still relies on manual extraction and entry of critical fields such as vendor identifiers, invoice numbers, line items, tax values, quantities, and totals. Manual processing is repetitive, time-consuming, and highly vulnerable to human error. Even small inconsistencies—such as incorrect tax extraction, duplicated invoice IDs, or misread totals—can propagate downstream into inventory mismatch, delayed payment cycles, and reconciliation failures. These issues become more pronounced in supply chain environments where document volume is high and timely processing directly affects logistics and business continuity.

Traditional Optical Character Recognition (OCR) systems were introduced to reduce manual effort, but

their effectiveness in real-world supply chain settings remains limited. OCR performs reasonably well on clean, template-consistent printed documents. However, invoices encountered in operational environments rarely satisfy such assumptions. Layout variation, low-resolution scans, skewed images, nested tables, handwritten entries, and vendor-specific formatting often degrade extraction quality. More importantly, OCR fundamentally performs character-level transcription rather than semantic interpretation. It may correctly read numeric tokens while still failing to determine whether a value corresponds to a unit price, subtotal, tax amount, or final payable total. Thus, the core limitation is not merely text recognition, but lack of contextual understanding.

Recent advances in transformer-based language models have significantly improved machine understanding of language, context, and sequence dependencies. Models derived from the generative pretraining paradigm—particularly the architecture introduced in Attention Is All You Need—have shown strong performance across natural language understanding and generation tasks. Large-scale autoregressive models such as GPT-2 are capable of learning semantic relationships, long-range dependencies, and contextual patterns that are difficult for rule-based OCR systems to capture.

However, deploying large language models directly in production-oriented supply chain applications introduces a different challenge. High-capacity models provide stronger reasoning ability but require substantial memory, computational power, and inference time. From your project presentation, GPT-2 Large contains approximately 774 million parameters and requires around 3.1 GB of storage, while DistilGPT2 contains only 82 million parameters, offering significantly faster inference and much lower memory requirements. Yet this efficiency comes with reduced contextual coherence and weaker semantic fidelity.

This trade-off between model quality and deployability is particularly important in document intelligence systems. Supply chain applications demand not only high extraction accuracy but also fast response times, scalable inference, and practical deployment constraints. A highly accurate but computationally expensive model may not be viable in environments where thousands of invoices must be processed daily or where low-latency interaction is required through dashboard and chat interfaces.

To address this challenge, this work explores knowledge distillation as the central methodological foundation. Knowledge distillation is a model compression paradigm in which a smaller student model learns to imitate the behavior of a larger teacher model. Rather than learning only from discrete ground-truth labels, the student also learns from the soft probability distribution produced by the teacher. These soft targets encode richer information about semantic similarity, token ranking, and contextual uncertainty. In effect, distillation allows the student model to inherit a significant portion of the teacher's representational knowledge while remaining computationally lightweight.

In this project, a custom domain-adapted language model is developed by combining the strengths of GPT-2 Large as the teacher and DistilGPT2 as the student. The objective is not merely generic language compression, but targeted adaptation for supply-chain invoice understanding. The distilled student is further fine-tuned on invoice-oriented textual and structured data so that it learns domain-specific patterns such as vendor naming conventions, line-item semantics, numerical dependencies, and financial field relationships. This creates a custom lightweight GPT model that is better aligned with invoice extraction and intelligent querying tasks than either off-the-shelf base model alone.

II. LITERATURE SURVEY

The field of document intelligence and automated invoice processing has been shaped by a series of progressive advancements in machine learning, natural language processing, and computer vision. This section reviews the key works that have directly influenced the design of the proposed system, spanning optical character recognition, transformer-based language models, retrieval-augmented generation, knowledge distillation, and anomaly detection in supply chains.

A. OCR-Based Document Processing

Smith and Lee [4] provided a foundational survey of OCR systems in document processing environments. Their work established that template-based OCR

achieves high accuracy on standardized printed documents but degrades considerably under layout variation, low-resolution scanning, and the presence of handwritten annotations. Subsequent research by Bukhari et al. (2012) introduced adaptive preprocessing pipelines that apply binarization, deskewing, and noise filtering prior to OCR, partially mitigating these limitations. However, these methods remain fundamentally character-level transcription systems lacking the semantic understanding required for accurate invoice field classification.

B. Transformer-Based Language Models

The seminal work by Vaswani et al. [2] introduced the Transformer architecture, which replaced recurrent structures with self-attention mechanisms, enabling models to capture long-range dependencies in text. This architecture became the foundation for a new generation of language models. Radford et al. (2019) subsequently introduced GPT-2, demonstrating strong zero-shot performance on diverse NLP tasks. Brown et al. [1] further scaled this paradigm to GPT-3, showing that few-shot learning with large-scale pretrained models could match or exceed task-specific fine-tuned systems. These developments highlighted both the potential and the computational burden of large language models in real-world applications.

C. Vision-Language Models for Document Understanding

Xu et al. (2020) proposed LayoutLM, which combined textual tokens with 2D positional information derived from OCR bounding boxes, enabling joint modeling of text and layout for document understanding tasks. This was extended in LayoutLMv2 (Xu et al., 2021), which additionally incorporated visual features from document images using a unified multimodal Transformer. Huang et al. (2022) further introduced LayoutLMv3, achieving state-of-the-art results across document AI benchmarks by unifying masked text and image modeling. These Vision-Language Models (VLMs) demonstrated that combining visual layout signals with textual semantics significantly improves performance on structured document tasks such as key information extraction and document classification, directly informing the hybrid extraction approach used in the proposed system.

D. Retrieval-Augmented Generation

Lewis et al. [3] introduced the Retrieval-Augmented Generation (RAG) framework, which augments a generative language model with a non-parametric retrieval component. By conditioning text generation on documents retrieved from an external corpus, RAG substantially improves factual accuracy and reduces hallucination in knowledge-intensive tasks. Karpukhin et al. (2020) proposed Dense Passage Retrieval (DPR), providing an effective mechanism for mapping queries and documents into a shared embedding space for efficient similarity search. Subsequent work by Izacard and Grave (2021) demonstrated that fusing multiple retrieved passages further improves answer generation quality. These findings directly motivated the semantic retrieval and vector similarity search components adopted in the proposed query pipeline.

E. Knowledge Distillation

Hinton et al. (2015) introduced knowledge distillation as a model compression technique in which a compact student model is trained to reproduce the soft probability distributions of a larger teacher model. This approach was shown to significantly narrow the performance gap between large and small models while greatly reducing inference cost. Sanh et al. (2019) applied distillation to BERT, producing DistilBERT—a model retaining approximately 97% of BERT's language understanding capability at 60% of its size. In the generative domain, relevant work on DistilGPT2 demonstrated comparable compression gains for autoregressive models. Sun et al. (2020) further proposed task-specific distillation strategies that combine intermediate-layer supervision with output distribution matching, improving student performance on targeted NLP benchmarks. These works collectively established the theoretical and practical foundation for the teacher-student distillation methodology employed in this project.

F. Anomaly Detection and Knowledge Graphs in Supply Chains

Chandola et al. (2009) provided a comprehensive taxonomy of anomaly detection methods, classifying approaches into statistical, proximity-based, and classification-based categories. In the financial and supply chain context, Ngai et al. (2011) surveyed machine learning applications for fraud detection,

demonstrating that graph-based representations are particularly effective for identifying irregular transaction patterns. More recently, Ji et al. (2021) explored the integration of knowledge graphs with entity recognition systems to improve structured information extraction from business documents. These works informed the design of the Supply Chain Knowledge Graph component, which serves as the basis for the anomaly detection module in the proposed ingestion pipeline.

G. Summary and Research Gap

While existing literature has addressed individual components of document intelligence—including OCR, layout-aware document modeling, retrieval-augmented generation, and knowledge distillation—no prior work has unified these components into a coherent end-to-end pipeline specifically designed for supply chain invoice processing. Existing systems either focus on extraction without providing intelligent querying capabilities, or they employ large, computationally expensive models that are impractical for production deployment. The proposed system addresses this gap by integrating hybrid extraction, semantic retrieval, anomaly detection, and compressed language modeling into a single, cohesive architecture optimized for the invoice domain.

III. MOTIVATION

The motivation for this work arises from the practical limitations observed in existing invoice processing systems. During initial experimentation with OCR-based solutions, it became evident that these systems perform well only under ideal conditions where documents are clean, structured, and standardized. However, real-world invoices exhibit significant variability in layout, formatting, language, and quality, rendering traditional methods inadequate.

Another key limitation lies in the inability of existing systems to understand context. While OCR tools can extract textual content, they do not capture relationships between fields. As a result, critical information such as totals, tax values, or vendor details may be misinterpreted or incorrectly associated. This reduces the usability of extracted data and necessitates manual verification.

Additionally, accessibility emerged as an important concern. Many systems require technical expertise to query and analyze stored data, limiting their usability for non-technical stakeholders. This creates a barrier to adoption in small and medium enterprises, where resources and technical expertise may be limited.

These observations motivated the development of a system that combines intelligent extraction with natural language querying, enabling users to interact with data intuitively. Furthermore, the need for real-time deployment and scalability led to the incorporation of knowledge distillation techniques to reduce model size and computational requirements without sacrificing performance.

IV. PROBLEM STATEMENT

Existing invoice processing systems are characterized by inefficiencies and limitations that hinder their effectiveness in real-world applications. Manual data entry is time-consuming and prone to human error, especially when dealing with large volumes of documents. OCR-based systems, while automated, fail to handle complex layouts and lack contextual understanding, resulting in inaccurate data extraction.

Moreover, these systems do not provide mechanisms for validating extracted data, allowing errors such as incorrect totals or missing fields to go undetected. The absence of intelligent querying capabilities further complicates data access, as users must rely on technical knowledge to retrieve information from databases.

The core problem addressed in this research is the development of a robust, intelligent system capable of accurately extracting, validating, storing, and querying invoice data in a scalable and user-friendly manner. The system must handle diverse document formats, minimize errors, and enable seamless interaction through natural language interfaces while maintaining computational efficiency.

V. PROPOSED SYSTEM

The proposed system is designed as a modular and scalable document intelligence pipeline that automates invoice processing and enables intelligent querying over structured data. The architecture is divided into two primary components: the Ingestion Pipeline and the Query Pipeline, which together enable end-to-end transformation from unstructured documents to actionable insights.

The Ingestion Pipeline is responsible for processing raw invoice documents and converting them into structured, validated, and searchable data. The Query Pipeline, on the other hand, enables users to interact with this data using natural language queries through a Retrieval-Augmented Generation (RAG) framework.

VI. IMPLEMENTATION

5.1 OVERALL SYSTEM ARCHITECTURE

The system is implemented as a modular pipeline consisting of two primary components: the ingestion pipeline and the query pipeline. The ingestion pipeline is responsible for processing incoming documents, while the query pipeline handles user interactions and information retrieval. These pipelines are interconnected through a centralized database and embedding layer, ensuring seamless data flow and consistency.

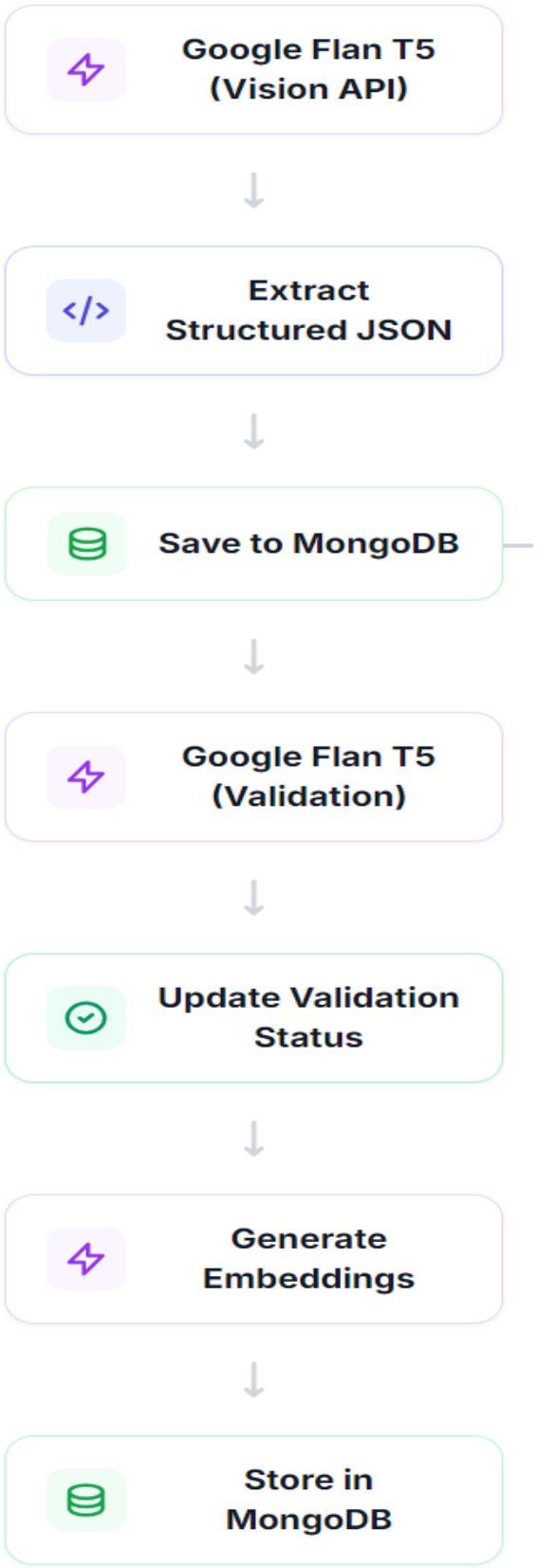
The ingestion pipeline begins with document upload, followed by preprocessing steps such as image enhancement, orientation correction, and noise reduction. The processed document is then passed to the extraction engine, which employs a hybrid approach combining OCR and Vision-Language Models. Extracted data is structured into JSON format, validated for consistency, and stored in a MongoDB database. Subsequently, embeddings are generated to enable semantic search.

The query pipeline operates on user input, converting queries into embeddings and retrieving relevant data using similarity search. The retrieved context is then passed to a language model, which generates a coherent and context-aware response.

5.2 INGESTION PIPELINE

The ingestion pipeline handles the transformation of raw invoices into structured knowledge. It consists of multiple sequential stages.

The process begins with the Document Upload Interface, which allows users to upload invoices in various formats such as images and PDFs. To ensure robustness against real-world data variations, a preprocessing stage is applied to enhance image quality through noise reduction, alignment correction, and contrast enhancement.



The core of the ingestion pipeline is the Hybrid Extraction Engine, which combines traditional OCR with Vision-Language Models. While OCR extracts textual content, the Vision-Language model captures structural and contextual relationships within the document. This hybrid approach enables accurate extraction of key invoice fields such as vendor details, item lists, tax values, and total amounts, even in complex and non-standard layouts.

The extracted information is then converted into a standardized JSON format, ensuring consistency across different invoice types. Following this, a validation module performs consistency checks, including total verification, duplicate detection, and missing field identification. Advanced anomaly detection is further supported using a Supply Chain Knowledge Graph, enabling identification of fraudulent patterns and irregular transactions.

Finally, the validated data is stored in a MongoDB database. The database design supports flexible schema handling, making it suitable for semi-structured invoice data. In addition to structured data, embeddings are generated and stored to enable semantic retrieval in later stages.

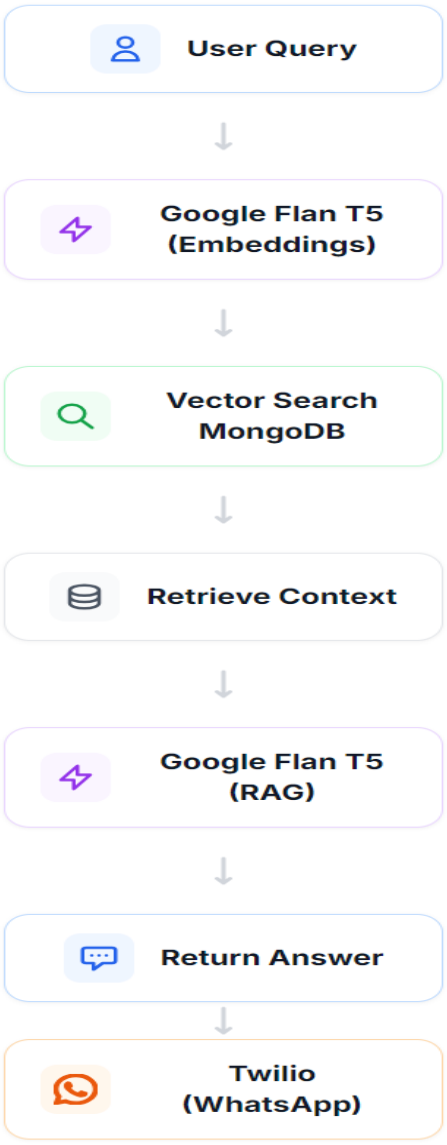
5.3 QUERY PIPELINE

The query pipeline enables natural language interaction with the stored invoice data using a Retrieval-Augmented Generation (RAG) approach.

Users interact with the system through a chat-based interface, where queries are expressed in natural language. These queries are first converted into vector embeddings and matched against stored embeddings to retrieve relevant invoice data.

The retrieved context is then passed to a custom knowledge-distilled GPT model, which generates responses grounded in actual data. Unlike traditional generation models, the RAG framework ensures that responses are factually accurate and contextually relevant by restricting generation to retrieved information.

The query pipeline operates through three main stages, beginning with the encoding of user queries into embeddings, followed by the semantic retrieval of relevant data, and culminating in context-aware response generation using the distilled model. This design removes the reliance on manual database queries and enables non-technical users to efficiently access complex information.



5.4 USER INTERFACE LAYER

The system includes an integrated user interface consisting of a dashboard and a chat module.

The dashboard provides a visual overview of processed invoices, system activity, and detected anomalies. It enables users to monitor operations and quickly identify inconsistencies.

The chat interface allows users to interact with the system conversationally, enabling intuitive querying and real-time insights. This significantly improves accessibility for users without technical expertise.

VII. METHODOLOGY

This section presents the design and training methodology of the proposed custom distilled language model, which forms the core of the intelligent query system. The objective is to achieve a balanced trade-off between performance and efficiency by transferring knowledge from a large, high-capacity transformer model to a compact, deployable architecture, and subsequently adapting it to the invoice processing domain.

6.1 MOTIVATION MODEL COMPRESSION

Transformer-based language models have shown remarkable performance in natural language understanding and generation. Large-scale models such as GPT-2 Large are particularly effective at modeling long-range dependencies within text, enabling them to capture both semantic meaning and syntactic structure with high fidelity. As a result, these models are capable of generating coherent, context-aware responses that reflect a deep understanding of language. Such capabilities are especially beneficial in document intelligence tasks, where accurately interpreting relationships between elements like invoice totals, line items, and taxes depends on contextual reasoning rather than straightforward text extraction.

However, the deployment of such models in real-world systems introduces several practical constraints. Large models incur high computational cost, require significant memory (on the order of gigabytes), and exhibit high inference latency, making them unsuitable for real-time applications such as interactive query systems or large-scale enterprise deployment.

On the other hand, lightweight models such as DistilGPT2 offer improved efficiency. They are significantly smaller, faster during inference, and require fewer computational resources. Despite these advantages, they suffer from limitations including reduced contextual depth, lower coherence in generated text, and weaker semantic understanding.

This creates a fundamental trade-off between model capacity and deployability. To address this, the proposed work adopts a knowledge distillation approach to construct a custom model that retains the reasoning capability of GPT-2 Large while achieving the efficiency of DistilGPT2. The goal is not merely compression, but performance-preserving compression tailored to the invoice domain.

6.2 KNOWLEDGE DISTILLATION

Knowledge distillation is applied as a supervised training paradigm in which a student model is trained to emulate the behavior of a more powerful teacher model. In this work, the teacher model (T) is GPT-2 Large, which provides high-quality contextual predictions, while the student model (S) is initialized from DistilGPT2 and further extended. The primary objective is to enable the student model to approximate the function learned by the teacher. Instead of depending solely on labeled training data, the student leverages both the ground truth labels and the output distribution produced by the teacher.

The core idea underlying this approach is that the teacher model encodes rich structural and semantic information within its output probability distributions. By learning from these distributions, the student model is able to acquire knowledge that is not explicitly captured in the training labels, leading to improved generalization and performance.

The training process therefore involves two complementary learning signals:

- Hard targets, which correspond to the actual ground truth labels
- Soft targets, which correspond to the probability distribution produced by the teacher model

This dual supervision enables the student model to generalize better and mimic the behavior of the teacher more effectively than traditional training methods.

6.3 SOFT TARGET LEARNING AND TEMPRATURE SCALING

In standard classification or language modeling, output probabilities are computed using the softmax function over logits. In knowledge distillation, this process is modified using a temperature scaling parameter (T) to produce softer probability distributions.

$$P_i = \frac{e^{z_i/T}}{\sum_j e^{z_j/T}}$$

Here, z_i represents the logits produced by the model, and T is the temperature parameter. When $T = 1$, the softmax behaves normally. However, when $T > 1$, the output distribution becomes smoother, assigning non-negligible probabilities to less likely tokens.

This smoothing effect plays a crucial role in effective knowledge transfer. A standard softmax distribution is typically highly peaked, revealing only the most probable token, whereas increasing the temperature produces a softer distribution that highlights the relative probabilities of multiple tokens. This allows the model to capture inter-token relationships, understand semantic similarities between candidate outputs, and retain the implicit linguistic structure learned by the teacher.

By training on these softened probability distributions, the student model learns not just the correct prediction but also the relative importance of alternative predictions. As a result, it achieves better generalization and develops richer representations, which is particularly valuable for tasks requiring nuanced language understanding, such as invoice interpretation.

6.4 LOSS FUNCTION DESIGN

To effectively combine information from both hard and soft targets, the training objective uses a composite loss function.

Distillation Loss

The discrepancy between the teacher and student probability distributions is measured using Kullback–Leibler (KL) divergence:

$$L_{KD} = KL(P_T \parallel P_S)$$

This loss encourages the student model to mimic the output behavior of the teacher.

Cross-Entropy Loss

The standard cross-entropy loss is used to ensure correctness with respect to ground truth labels:

$$L_{CE} = -\sum y \log (P_S)$$

Combined Objective

The final loss function is a weighted combination of the two:

$$L = \alpha L_{CE} + (1 - \alpha) L_{KD}$$

Here, $\alpha$is a hyperparameter that controls the balance between direct supervision and teacher imitation. A higher value of αemphasizes learning from labeled data, while a lower value increases reliance on the teacher's knowledge.

This formulation ensures that the student model remains grounded in actual data while benefiting from the richer supervision signal provided by the teacher.

6.5 CUSTOM GPT ARCHITECTURE

Rather than directly using DistilGPT2, the proposed system constructs a custom hybrid student architecture tailored for document intelligence tasks.

The model is initialized with DistilGPT2 weights to leverage its efficiency and pretrained linguistic knowledge. Knowledge distilled from GPT-2 Large is then incorporated during training to enhance its contextual reasoning capabilities.

Several architectural adaptations are introduced to better specialize the model for invoice processing. Domain-adaptive token embeddings are incorporated to improve the representation of invoice-specific vocabulary, including financial terms, vendor names, and numerical patterns. In addition, the context window is optimized to effectively capture structured relationships within invoices, such as the connections between line items and overall totals.

The attention mechanisms are further fine-tuned to emphasize key aspects of the task, including numerical reasoning—for instance, handling totals and tax calculations—as well as entity extraction, such as identifying vendor names and invoice IDs. Together, these modifications enable the model to better understand the hierarchical and relational structure inherent in invoice data, which is essential for accurate extraction and reasoning.

6.6 FINE TUNING ON DOMAIN DATA

Following the distillation phase, the student model undergoes domain-specific fine-tuning to adapt it to invoice-related tasks. The training data includes raw invoice text, structured JSON representations, and natural language queries paired with their corresponding responses, ensuring exposure to both unstructured and structured formats.

The fine-tuning process is designed to align the model with real-world use cases by improving the accuracy of field extraction, enhancing its ability to understand user queries, and enabling it to generate contextually accurate responses. To achieve this, multiple task formulations are incorporated during training. These include sequence-to-sequence learning for mapping invoice text to structured outputs, question answering over invoice data, and contextual summarization for generating concise insights.

By leveraging this multi-task training strategy, the model is able to develop both strong extraction

capabilities and deeper reasoning skills, making it well-suited for complex document intelligence tasks.

6.7 INTEGRATION WITH RAG PIPELINE

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VIII. EXPERIMENTAL RESULTS

This section provides a comprehensive evaluation of the proposed custom knowledge-distilled GPT model, with a focus on its ability to balance language quality, computational efficiency, and practical deployability. The analysis compares three models: GPT-2 Large as the teacher model, DistilGPT2 as the baseline student model, and the custom distilled model as the proposed approach.

The experiments are designed to assess both architectural efficiency and the quality of language generation, particularly in the context of invoice-related tasks such as query answering, summarization, and contextual reasoning.

7.1 MODEL COMPARISON

The architectural and performance characteristics of the three models are summarized in Table 1.

Metric	GPT-2 Large	DistilGPT2	Custom Distilled Model
Parameters	774M	82M	~100–150M
Coherence	Very High	Moderate	High
Latency	High	Low	Low
Memory Usage	~4GB	<500MB	~700MB
Deployment Feasibility	Difficult	Easy	Practical

Analysis

The comparison highlights the inherent trade-offs between model size and performance:

- GPT-2 Large demonstrates superior coherence and contextual understanding due to its large parameter space. However, it incurs significant computational overhead, making it impractical for real-time or large-scale deployment.
- DistilGPT2 offers substantial improvements in efficiency, with reduced memory footprint and faster inference. However, this comes at the cost of reduced coherence and weaker semantic representation, particularly in domain-specific tasks.
- The Custom Distilled Model achieves a balanced architecture, maintaining high coherence while significantly reducing resource requirements. By selectively transferring knowledge from the teacher model and incorporating domain-specific fine-tuning, it bridges the gap between performance and efficiency.

In particular, the custom model reduces memory usage by approximately 80–85% compared to GPT-2 Large, while preserving most of its reasoning capability. At the same time, it introduces only a moderate increase in resource usage compared to DistilGPT2, making it suitable for deployment in production systems.

7.2 LANGUAGE QUALITY METRICS

To quantitatively evaluate language generation performance, standard NLP metrics are used, including ROUGE-L, BLEU, and Cosine Similarity. These metrics capture different aspects of text quality, such as recall, precision, and semantic similarity.

Metric	GPT-2 Large	DistilGPT2	Custom Model
ROUGE-L	~0.40	~0.32	~0.37
BLEU	~20	~15	~18
Cosine Similarity	~0.90	~0.84	~0.88

Metric Interpretation

- ROUGE-L (Longest Common Subsequence) Measures the ability of the model to capture long-range dependencies and sequence overlap with reference outputs.
  - GPT-2 Large performs best due to its strong contextual modeling.
  - DistilGPT2 shows reduced performance due to limited depth.
  - The custom model achieves near-teacher performance, indicating successful transfer of structural knowledge.
- BLEU Score (n-gram precision) Evaluates how closely generated text matches reference phrases.
  - Lower scores in DistilGPT2 indicate missing connectors and slight phrasing inconsistencies.
  - The custom model improves precision, demonstrating better phrase-level generation.
- Cosine Similarity (Semantic similarity) Computed using embedding-based representations (e.g., SBERT), these metric measures semantic alignment.
  - All models perform relatively well, but the custom model retains most of the semantic understanding of GPT-2 Large.

Key Insight

The custom distilled model consistently achieves performance closer to GPT-2 Large than DistilGPT2, confirming that knowledge distillation effectively preserves semantic and contextual information.

7.3 OBSERVATION AND DISCUSSION

The experimental findings indicate that knowledge distillation effectively transfers critical capabilities from the teacher model to the student model while substantially reducing computational complexity. The custom distilled model demonstrates a strong ability to interpret context, understand relationships between invoice fields, and generate coherent, meaningful responses. This suggests that semantic understanding—typically associated with large-scale models such as GPT-2 Large—is largely preserved despite the reduction in parameter size.

A major contributor to this performance is the use of soft target learning during distillation. By learning from the probability distributions produced by the teacher model, the student captures nuanced relationships between tokens rather than relying solely on discrete ground truth labels. This enables improved generalization across variations in input data and results in more natural, contextually appropriate outputs. Consequently, the distilled model achieves not only parameter compression but also retains the functional behavior and reasoning patterns of the teacher.

Beyond distillation, domain-specific fine-tuning plays a crucial role in further enhancing performance. Training the model on invoice-related data, including structured representations and natural language queries, aligns it closely with task-specific requirements. This leads to improved recognition of financial entities such as totals, tax values, and vendor details, as well as a better understanding of structured relationships like the association between line items and aggregate values. Fine-tuning also strengthens the model's ability to interpret user queries and generate accurate, context-aware responses, effectively transforming it from a general-purpose language model into a specialized system for document intelligence.

From a systems perspective, the custom model achieves a strong balance between performance and efficiency. While GPT-2 Large offers superior language quality, its high computational cost limits practical deployment. In contrast, DistilGPT2 provides efficiency but at the expense of coherence and semantic precision. The proposed model bridges this gap by delivering near-teacher-level language quality while maintaining low inference latency and moderate memory usage. This balance supports real-time interaction and makes the system suitable for deployment in resource-constrained environments, while also improving scalability for handling large data volumes.

The benefits of the custom model become even more pronounced when integrated into a Retrieval-Augmented Generation pipeline. Faster inference speeds enhance the efficiency of retrieval-response cycles, enabling near real-time query processing, while preserved contextual understanding improves the relevance and accuracy of generated outputs. By

grounding responses in retrieved data rather than relying solely on internal knowledge, the system produces outputs that are both factually accurate and contextually appropriate. This combination of speed, accuracy, and reliability makes it well-suited for applications such as supply chain analytics, inventory management, and financial auditing.

Overall, the evaluation confirms that the proposed custom distilled model successfully bridges the gap between large and small language models, achieving high-quality language generation while significantly reducing computational cost. These results underscore the effectiveness of combining knowledge distillation with domain-specific fine-tuning to build efficient, scalable AI systems for real-world applications.

IX. CONCLUSION

This implementation demonstrates a comprehensive integration of document intelligence, semantic retrieval, and model optimization techniques. By combining advanced AI models with practical system design, the proposed solution addresses key challenges in invoice processing and provides a scalable framework for supply chain automation.

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