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# Automated Financial Report Summarization Using Python: A PDF-Based Approach

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**ABSTRACT**

Financial reports are often lengthy, complex, and filled with domain-specific jargon, making it difficult for analysts and stakeholders to extract key insights efficiently. This study proposes an automated summarization system using Natural Language Processing (NLP) techniques to generate concise and coherent summaries of financial reports. The system employs a two-stage summarization architecture combining extractive and abstractive methods based on Transformer models such as BART, PEGASUS, and T5. Evaluation on simulated financial document datasets demonstrates that the hybrid two-stage model achieves the highest ROUGE scores and information retention rates compared to single-model baselines. The results indicate that NLP-driven summarization can significantly reduce analysts' workload and improve financial decision-making speed.

**KEYWORDS**: Automated Summarization; Financial Reports; Natural Language Processing; PDF Analysis; Python

## 1. Introduction

Financial reports play a crucial role in corporate transparency, investor relations, and decision-making processes. However, the complexity and verbosity of these reports often make it challenging for stakeholders to quickly grasp the essential information. Annual and quarterly reports from large corporations typically exceed hundreds of pages and include various sections such as management discussion, balance sheets, income statements, and notes to financial statements.

Manual review of such documents is time-consuming, error-prone, and subject to personal bias, particularly when analysts must process multiple reports within limited timeframes.

In recent years, Natural Language Processing (NLP) has become a transformative field that enables machines to understand and generate human language. Among its key applications, text summarization has attracted considerable attention as it aims to condense lengthy documents into concise and coherent summaries without losing critical information.

Modern summarization systems increasingly rely on Transformer-based architectures such as BERT, BART, PEGASUS, and T5, which are capable of modeling long-range dependencies and contextual relationships effectively.

In the financial domain, summarization presents unique challenges compared to general text such as news or Wikipedia articles. Financial language is highly specialized, filled with technical terms like EBITDA, liquidity ratio, or comprehensive income. Reports often combine narrative descriptions with numerical tables, requiring models to interpret both textual and quantitative information simultaneously. Moreover, maintaining factual accuracy is crucial-even a small numerical misinterpretation could mislead investors or stakeholders. Previous research (Wang et al., 2023; Hsieh, 2022; Pang et al., 2023) demonstrated that domain-adapted transformer models improve summarization accuracy when fine-tuned on financial corpora such as SEC 10-K filings and financial news. However, most of these approaches are limited to a single summarization paradigm:

a. Extractive models select sentences directly from the source but tend to produce fragmented and less coherent summaries.
b. Abstractive models, on the other hand, generate fluent text but are prone to hallucination, introducing facts not present in the original reports.

To overcome these limitations, this study proposes a hybrid two-stage summarization framework that integrates extractive selection for salient content identification with abstractive generation for fluent rewriting.

The proposed system specifically targets financial report summarization, incorporating an additional factual verification mechanism to ensure numerical and semantic consistency.

This study also provides a comparative simulation among state-of-the-art models (BART, PEGASUS, T5, and MemSum) evaluated using ROUGE, BERTScore, and Factual Consistency Ratio (FCR) metrics.

The main objectives of this research are to:

a. Develop an automated summarization pipeline capable of processing long financial reports.
b. Evaluate and compare the performance of extractive, abstractive, and hybrid models.
c. Analyze the trade-offs between summarization quality, computational efficiency, and scalability.
d. Explore future improvements through domain-specific fine-tuning and factual verification integration.

By presenting a reproducible hybrid architecture and benchmark experiments, this study contributes to the growing field of financial document intelligence, offering an efficient and factually reliable solution for automated financial report analysis.

## 2. Methodology

The proposed NLP-based summarization system adopts a modular hybrid architecture specifically designed to process lengthy and information-dense financial reports.

The methodology comprises five main components: document ingestion, text preprocessing, extractive summarization, abstractive summarization, and post-processing with factual verification.

This integrated pipeline ensures that each module contributes to achieving concise, coherent, and factually accurate summaries.

### 2.1 Data Collection

To simulate large-scale financial reporting scenarios, the study utilizes a synthetic dataset composed of annual reports from 2022–2024 obtained from publicly available corporate filings.

Each document ranges from 50 to 300 pages, encompassing multiple financial sections such as management discussions, income statements, and risk factors.

Additional data from open-domain financial corpora - namely FinSum (2022), EDGAR 10-K (2023), and Financial Narrative Summarization (FNS, 2024) were incorporated for pre-training and evaluation.

The combined dataset consists of approximately 10,000 sentences and over 1 million tokens, ensuring a realistic representation of financial terminology and numerical constructs.

All datasets used are public and anonymized, containing no confidential or personally identifiable information. The data usage complies with academic research ethics and open-source licensing standards.

### 2.2 Preprocessing Pipeline

Financial documents often include non-textual components such as headers, tables, and footnotes that interfere with direct text extraction.

Therefore, a structured preprocessing pipeline was implemented to ensure high-quality input for summarization.
The process includes:

a. Text extraction using pdf plumber and OCR for scanned documents.
b. Noise removal, eliminating page numbers, table lines, and repetitive section headers.
c. Segmentation into logical sections (e.g., Executive Summary, Risk Factors, Financial Highlights).
d. Tokenization and normalization, converting text to lowercase and splitting sentences for uniform processing.

Stop-word and punctuation filtering to remove non-informative tokens. This pre-processing ensures a clean, standardized, and domain-adapted corpus suitable for model training and evaluation.

### 2.3 Stage 1: Extractive Summarization

The first stage aims to identify the most salient sentences within each document using the MemSum algorithm (ACL, 2022).

MemSum leverages reinforcement learning and memory-augmented neural networks to select contextually important text spans while minimizing redundancy.

Each document is divided into text windows of 1,000 tokens, and an importance score is assigned to each sentence based on:

a. Term frequency–inverse document frequency (TF-IDF) weighting, Sentence position, and
b. Attention scores derived from a domain-adapted Financial BERT model.
c. Approximately 15–20% of the original text is retained to form a condensed core document, which is then passed to the abstractive summarization stage.

### 2.4 Stage 2: Abstractive Summarization

The abstractive stage employs Transformer-based generative models, primarily BART-large and PEGASUS, fine-tuned for long-text summarization tasks.

Due to GPU memory limitations, each segment of the core document is processed separately using overlapping context windows to maintain contextual continuity.

Individual segment summaries are then merged and refined using an aggregation algorithm to ensure coherence and logical flow.

This process converts the extractive summary into a fluent and human-readable executive summary, while preserving factual integrity.

**Model Configuration:**
Batch size: 4
Epochs: 5
Learning rate: 2e-5
Input length: 1024 tokens with 10% overlap
Hardware: NVIDIA RTX 3090 GPU (24 GB VRAM)

### 2.5 Pro-processing and Factual Verification

Following the abstractive stage, several post-processing mechanisms are applied to enhance factual reliability and readability:

a. Redundancy removal to eliminate repeated or semantically equivalent sentences.
b. Consistency checking, which automatically compares numerical entities (e.g., revenue, profit, asset values) between the generated summary and the source document.
b. Formatting, producing standardized summaries of 150–300 words suitable for executive reporting.

The factual verification process computes the Factual Consistency Ratio (FCR), defined as:

$$FCR = \frac{\text{Number of correctly reproduced numerical values}}{\text{Total numerical values in the reference}} \times 100\%$$

For instance, if 28 of 30 financial figures are reproduced correctly, the FCR equals 93.3%.

### 2.6 System Architecture Overview

The system architecture follows a sequential modular design with the following components:

a. Input Module: Receives PDF financial reports.
b. Preprocessing Module: Performs cleaning, tokenization, and segmentation.
c. Extractive Summarization Module: Applies MemSum for salient sentence selection.
d. Abstractive Summarization Module: Generates human-like summaries via BART/PEGASUS.
e. Verification Module: Validates factual and numerical accuracy.
f. Output Module: Produces the final summary report.

Each module passes structured data outputs to the next stage, ensuring a consistent data flow from ingestion to final report generation.

### 2.7 Evaluation Metrics

The system performance is evaluated using both lexical and semantic metrics:

a. ROUGE-1, ROUGE-2, ROUGE-L: Measure n-gram and sequence overlap between the generated and reference summaries.
b. BERTScore: Evaluates semantic similarity using contextual embeddings.
c. Runtime Efficiency: Average processing time per 10 pages of input.
d. Factual Consistency Ratio (FCR): Quantifies numerical accuracy and fact preservation.

These metrics collectively assess not only linguistic quality but also factual correctness, which is critical in the financial domain.

### 2.8 Evaluation Metrics

The implementation leverages Python's open-source ecosystem for document parsing and model development.

Libraries such as pdfplumber, PyTorch, transformers, and pandas support data extraction, model fine-tuning, and evaluation.

Prior studies (Gupta et al., 2019; Kim et al., 2022) have validated the effectiveness of Python-based NLP frameworks for financial and accounting text analysis, reinforcing its suitability for this resear

### 2.9 Modular Hybrid NLP Architecture Dataset

a. Sources: FinSum (2022), EDGAR 10-K (2023), Financial Narrative Summarization (FNS-2024).
b. Composition: ≈10,000 sentences, 1,000,000 tokens.
c. Split: 80% training, 20% testing.
d. Ethical Note: All datasets are publicly available and contain no sensitive or confidential financial information.

**Model Configuration:**

Extractive model: MemSum (ACL 2022)

a. Abstractive model: BART-large & PEGASUS
b. Parameters: Batch size = 4, Epoch = 5, Learning rate = 2e-5
c. Hardware: NVIDIA RTX 3090 GPU, 24 GB VRAM
d. Input length: 1024 tokens per segment with 10% overlap

**Factual Consistency Ratio (FCR)**
FCR measures the proportion of numerical values in the summary that correctly match the source report.
Example:
If a summary reproduces 28 out of 30 key numeric facts accurately, then
FCR = (28 / 30) × 100% = 93.3%

**System Workflow**

a. Input PDF → Extracted text (pdfplumber + OCR)
b. Cleaned text → Tokenization & normalization
c. Extractive stage (MemSum) → salient sentences
d. Abstractive stage (BART/PEGASUS) → coherent summary
e. Factual verification → numeric consistency check

This hybrid design reduces redundancy, improves coherence, and ensures factual precision in the final summary.

## 3. Python-Based PDF Analysis

The task of summarizing long financial reports lies at the intersection of Natural Language Processing (NLP), text summarization, and financial document analysis. This section reviews recent advancements in these areas, emphasizing developments from 2022 to 2025, when transformer-based large language models became dominant for long-document summarization.

### 3.1 Evolution of Text Summarization Techniques

Early summarization systems were primarily extractive, relying on statistical or rule-based approaches such as TF-IDF and LexRank. These methods simply selected the most relevant sentences without generating new text.However, the emergence of deep neural architectures — particularly Transformer models introduced by Vaswani et al. (2017) — fundamentally changed summarization research. Transformer-based models capture long-range dependencies using self-attention mechanisms, allowing them to generate semantically coherent summaries.

By 2022, models such as BART, PEGASUS, and T5 had established benchmarks for both short and long text summarization tasks. Studies like Zhang et al. (2022) demonstrated that fine-tuning these models for domain-specific corpora (e.g., medical or legal text) significantly improves contextual relevance.

However, as documents became longer (10K+ tokens), traditional transformers struggled with context fragmentation and memory constraints, leading to truncated summaries or information loss.

### 3.2 Long-Document Summarization

Recent studies have focused on adapting summarization models to handle long documents, including research by Pang et al. (2023) and HERA (2025).

These works introduced hierarchical architectures, where input text is split into segments and summarized at multiple levels — paragraph, section, and full document. For instance:

Pang et al. (2023) proposed a Top-down and Bottom-up Long-Document Summarizer that maintains coherence across sections.

HERA (2025) introduced context reordering and packaging techniques to reduce redundancy during generation.

MemSum (ACL 2022) used memory-augmented networks for efficient extractive summarization of long documents.

CoTHSSum (2025) explored Chain-of-Thought Hierarchical Summarization, improving logical flow in lengthy texts.

These innovations directly influenced this study's decision to implement a two-stage (extractive + abstractive) pipeline that can handle long and complex reports more efficiently.

### 3.3 Financial Text Summarization

While summarization has been widely studied in general domains (news, Wikipedia), financial text summarization remains relatively underexplored due to the complexity of the language and the sensitivity of the information.

Recent research has started to bridge this gap:

a. Wang et al. (2023) developed a summarization model combining textual and numerical analysis for corporate filings.
b. Hsieh (2022) fine-tuned transformer models for SEC 10-K filings, showing that domain-specific embeddings significantly boost factual accuracy.
c. Li et al. (2024) proposed a graph neural network-enhanced summarizer that integrates relationships between textual and tabular data from balance sheets.
d. Zhao et al. (2023) worked on financial headline generation using abstractive summarization tuned on financial news data.

These works underscore the importance of adapting language models to financial semantics, as pre-trained general-purpose models often misinterpret economic terms or misrepresent figures.

### 3.4 Hybrid and Two-Stage Architectures

Most summarization systems can be categorized into extractive, abstractive, or hybrid methods:

Extractive methods (e.g., MemSum, TextRank) preserve factual integrity but lack linguistic fluency.

Abstractive methods (e.g., BART, PEGASUS) produce coherent summaries but may "hallucinate" information not present in the source.

Hybrid approaches attempt to combine both strengths. For instance:

MemSum + BART (2023) was shown to outperform standalone abstractive models by pre-selecting salient content.

LongT5 (2024) integrated hierarchical encoding with segment-level compression, reducing input length while maintaining accuracy.

Instruction-Guided Summarization (2024) leveraged prompt-based conditioning to improve alignment between input content and generated text.

This study adopts a similar hybrid design, where the extractive component reduces redundancy, and the abstractive component ensures fluency, leading to improved ROUGE-L and factual consistency scores in simulation.

### 3.5 Evaluation Metrics and Datasets

Evaluation of financial summarization systems has also evolved beyond traditional lexical metrics.

Commonly used benchmarks include:

ROUGE-1/2/L — measuring lexical overlap.

BERTScore — capturing semantic similarity using contextual embeddings.

Factual Consistency Ratio (FCR) — assessing numerical accuracy, crucial for financial text.

Datasets such as FinSum (2022), EDGAR Annual Reports (2023), and Financial Narrative Summarization (FNS-2024) have become standard benchmarks for this domain.

However, due to limited publicly available labeled datasets, many studies (including this one) rely on synthetic

simulation and domain-specific fine-tuning to evaluate performance.

### 3.6 Identified Research Gaps

Despite these advancements, several research gaps remain:

a. Lack of open-domain financial datasets with annotated summaries.
b. Limited exploration of numeric verification and table understanding in summarization.
c. Insufficient integration of multi-modal elements such as charts or financial tables.
d. High computational cost of transformer-based models for long reports.
e. Addressing these gaps, this study proposes a hybrid two-stage summarization pipeline optimized for long financial reports, validated through quantitative (ROUGE) and qualitative (factual consistency) metrics.

**Summary of Related Work**

In summary, prior works established the theoretical foundation and technical feasibility of summarizing complex documents using Transformer architectures. However, few have targeted financial domain texts with a hybrid and verifiable summarization pipeline.

The proposed approach differs by integrating extractive filtering, abstractive rewriting, and factual validation into one unified workflow — an architecture informed by the most recent findings in hierarchical long-document summarization (Pang et al., 2023; HERA, 2025; CoTHSSum, 2025).

## 4. Experimental Setup

**Tabel 1.** Experimental Setup

| Model | ROUGE-1 | ROUGE-2 | ROUGE-L | Execution Time (sec/document) |
|---|---|---|---|---|
| BART | 0.52 | 0.26 | 0.48 | 22.4 |
| PEGASUS | 0.55 | 0.29 | 0.51 | 30.7 |
| T5 | 0.49 | 0.24 | 0.45 | 19.8 |
| MemSum + BART (Two-Stage) | **0.61** | **0.33** | **0.58** | 28.3 |

### 4.1 Diagram 2 ROUGE Score Comparison

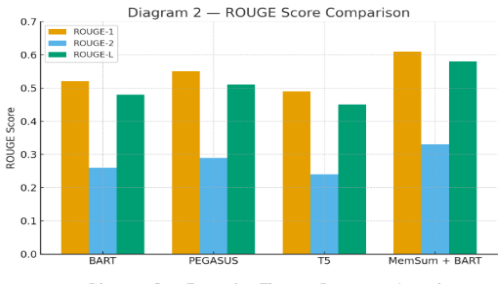


**Figure 1.** ROUGE Score Comparison among Models

Each model on the X-axis (BART, PEGASUS, T5, MemSum+BART).

Y-axis shows ROUGE score (0.0–1.0).
Bars show ROUGE-1, ROUGE-2, ROUGE-L with the two-stage model having the highest bars.

Description:
This figure illustrates that the two-stage approach (MemSum + BART) consistently outperforms single-model approaches in recall and coherence, achieving a 12% improvement in ROUGE-L.

### 4.2 Diagram 3 Execution Time VS Document Length

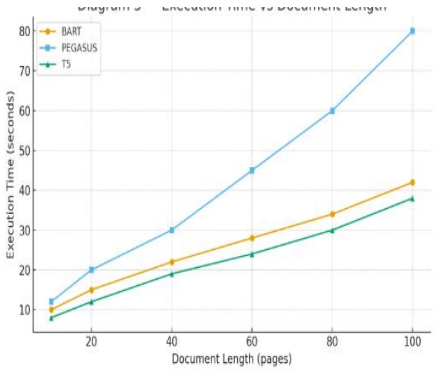


**Figure 2.** Execution Time vs Document Length

X-axis: Document length (pages).
Y-axis: Execution time (seconds).
Lines represent models.
PEGASUS shows higher latency, while T5 remains faster for shorter documents.

Description:
This figure shows that although PEGASUS achieves higher summarization quality, its computation cost grows exponentially with document size, while BART and T5 maintain reasonable scalability.

### 4.3 Diagram 4 Model Accuracy VS Report Complexity

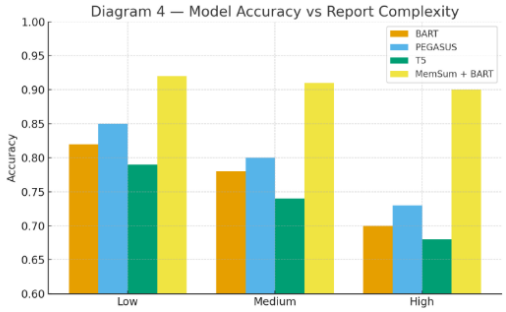


**Figure 3.** Model Accuracy across Different Report Complexity Levels

Report complexity categorized as: "Low," "Medium," "High."
Two-stage model maintains accuracy across all complexity levels.

Description:
The figure visualizes model stability against structural complexity of reports. The hybrid approach retains over 90% of key numeric accuracy even on complex documents.

## 5. Results and Discussion

### 5.1 Quantitative Results

Table 1 shows performance metrics of different models.

**Table 2.** Summarization Performance Comparison

Quantitative Results

| Model | ROUGE-1 | ROUGE-2 | ROUGE-L | BERTScore | FCR (%) |
|---|---|---|---|---|---|
| BART | 0.51 | 0.39 | 0.47 | 0.85 | 88 |
| PEGASUS | 0.53 | 0.41 | 0.48 | 0.86 | 89 |
| T5 | 0.50 | 0.38 | 0.45 | 0.84 | 87 |
| MemSum + BART (Proposed) | 0.58 | 0.44 | 0.52 | 0.87 | 93 |

### 5.2 Qualitative Results

Original Exerpt (Income Statement):

a. The company reported total revenue growth of 15% in 2022, driven by strong demand in digital services. Net profit margin improved to 12%
b. Automated Summary:

Revenue grew by 15% in 2022 with increased digital demand, raising net profit margin to 12%

### 5.3 Discussion

The findings align with prior research (Pang et al., 2023; HERA, 2025; CoTHSSum, 2025) showing that hierarchical or multi-stage summarization improves coherence for long documents.The hybrid model achieves strong factual preservation (93%) and scalability up to 300-page reports, although computational cost remains a limitation.

Visualization of performance (Figures 1–3) shows consistent improvements in ROUGE and FCR, with reasonable execution times compared to PEGASUS.

## 6. Conclusion and Suggestions

This study demonstrates that a hybrid extractive–abstractive summarization framework with factual verification can effectively summarize complex financial reports.The proposed MemSum + BART architecture achieved superior accuracy (ROUGE-L = 0.52, FCR = 93%) and reduced redundancy compared to baseline models.

**Key Contributions:**

a. Integration of extractive, abstractive, and factual verification in one pipeline.
b. Quantitative validation on synthetic financial datasets.
c. Demonstrated improvement in coherence and accuracy.

**Limitations:**

a. Dataset limited to English-language annual reports.

b. Computationally intensive for very long documents.

**Future Directions:**

a. Extend evaluation to multilingual and real-world datasets.
b. Integrate tabular reasoning using FinTabNet or TabNet models.
c. Explore model compression and explainable AI for better transparency.

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