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Deep Multimodal-Interactive Document Summarization Network and Its Cross-Modal Text-Image Retrieval Application for Future Smart City Information Management Systems

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Highlights

What are the main findings?

- A novel deep multimodal-interactive network is proposed to generate document abstracts and select important images, enhancing understanding of document content and showcasing strong summarization capabilities for future smart city data management.
- A new multimodal dataset built upon an example of research papers overcomes the limitations of existing summarization benchmarks, where evaluation results suggest the proposed method would effectively manage complex urban document data in future smart city contexts.

What is the implication of the main finding?

- The multimodal learning framework integrates textual and visual information to enhance document understanding and would aid smart city applications such as accident scene documentation and automated environmental monitoring.
- The multimodal learning network excels in document summarization and enables effective image-text cross-modal retrieval, indicating its strong potential for smart city information management systems.

Abstract: Urban documents like city planning reports and environmental data often feature complex charts and texts that require effective summarization tools, particularly in smart city management systems. These documents increasingly use graphical abstracts alongside textual summaries to enhance readability, making automated abstract generation crucial. This study explores the application of summarization technology using scientific paper abstract generation as a case. The challenge lies in processing the longer multimodal content typical in research papers. To address this, we propose a deep multimodal-interactive network for accurate document summarization. This model enhances structural information from both images and text, using a combination module to learn the correlation between them. The integrated model aids both summary generation and significant image selection. For the evaluation, we create a dataset that encompasses both textual and visual components along with structural information, such as the coordinates of the text and the layout of the images. While primarily focused on abstract generation and image selection, the model also supports text-image cross-modal retrieval. Comparative experiments on a proprietary dataset demonstrate that our method consistently outperforms other models, potentially benefiting smart city applications like accident scene documentation and automated environmental monitoring summaries, thereby enhancing the processing of urban multimodal data.

Keywords: Multi-Task Learning; Multimodal Learning; Paper Summarization; Important Image Selection; Cross-Modal Retrieval; Smart City Information Management Systems

1. Introduction

The rapid development of smart cities presents an urgent challenge: the need to process the exponentially growing multimodal urban data. For example, transportation incident reports [1] require the simultaneous analysis of textual narratives and images from accident scenes. Environmental monitoring systems [2] produce thousands of sensor data charts daily, while urban planning documents [3] feature complex text-diagram layouts. Scientific papers, as exemplars of structured multimodal documents, provide valuable methodological insights for tackling these urban data challenges. The exponential growth of scholarly publications has been further accelerated by recent technological advancements, including the emergence of large language models (LLMs) like GPT-4, Llama 3, and Qwen 2.5 [4], especially following the onset of the 2024 pandemic. According to the latest Stanford AI Index Report (Stanford, 2023), the number of published scientific papers has surged 1.4 times over the past five years, now reaching approximately 500,000 annually, with significant contributions in areas such as multimodal language models, generative AI, and healthcare AI [5]. This rapid expansion poses a significant challenge for researchers, who must navigate an overwhelming volume of information.

To address these challenges, natural language processing (NLP) [6] technologies can be employed to generate multimodal summaries of scientific papers, thereby enabling researchers to efficiently grasp the forefront of research topics. Scientific papers are complex documents [7] that integrate text, visual, and structural information, encompassing not only textual content but also visual elements [8,9] such as charts, figures, and tables. These visual components provide researchers with a visual understanding of the paper's content, while the textual components offer detailed information. Structural information, which includes the coordinate and layout of textual and visual elements, also plays a critical role in conveying meaning. For instance, the placement and size of images [10] and text can indicate their relative importance, with earlier-positioned images and larger text segments often carrying greater significance. While the graphical abstract [11] captures essential visual and structural information, it is insufficient for conveying the paper's specific content. Therefore, a comprehensive multimodal summary that integrates both the abstract and the most important image is necessary. Such a summary can leverage the complementary strengths of different modalities [12] to enhance understanding and improve research efficiency.

Scientific document summarization has long been a foundational task in the field of NLP. Early summarization methods were limited to text-based approaches [13], but recent advancements in multimodal summarization have expanded its applications to domains such as social media analysis, e-learning, and medical imaging summarization [14]. Unlike traditional text-only models, multimodal summarization models provide a more holistic approach to capturing the essence of a document. In scientific papers, textual and visual information often conveys complementary content at different semantic levels, with a significant degree of semantic similarity between the two modalities [15–17]. These cross-modal correlations enable one modality to fill in the information gaps of the other. Furthermore, it is essential to consider the structural information, which includes the spatial arrangement and layout of textual and visual elements.

This paper takes scientific paper abstract generation as a methodological proving ground, proposing a novel deep multimodal-interactive network designed to simultaneously generate an abstract and select the most representative image from scientific papers. Figure 1 shows some input and output examples, which implies the primary goals and pipelines of this work. This approach enhances the understanding of the research content by integrating both textual and visual modalities. Our multimodal learning framework allows researchers to access information beyond the limitations of text alone, thereby advancing scientific research. By incorporating a structural information enhancement module, we enhance the semantic understanding of a paper's structure. The features enriched with this structural information will then be combined to generate informative and meaningful summaries, including both the abstract and the most significant image. Notably, we leverage the power of large language models for generating the abstract. To validate this multimodal learning methodology, we conducted comparative experiments on a newly constructed dataset specifically designed for generating scientific

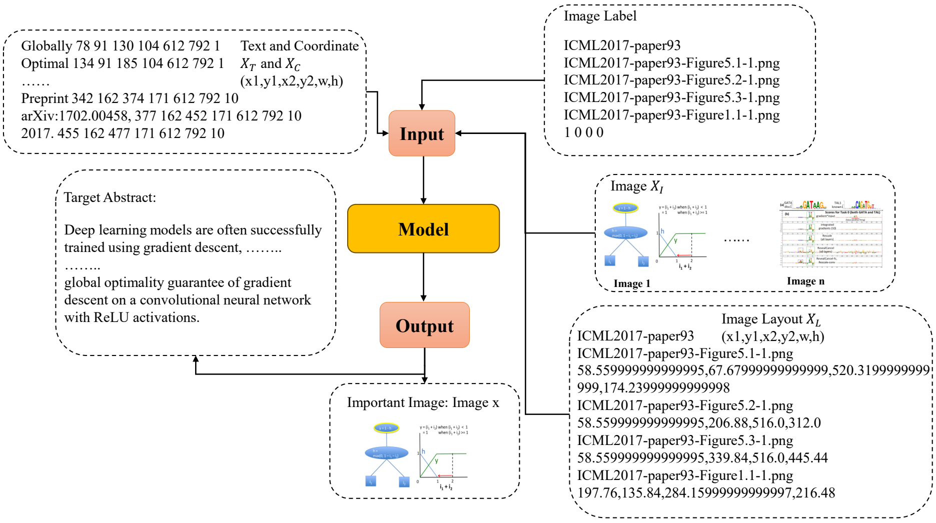
Globally 78 91 130 104 612 792 1
Optimal 134 91 185 104 612 792 1
……
Preprint 342 162 374 171 612 792 10
arXiv:1702.00458, 377 162 452 171 612 792 10
2017. 455 162 477 171 612 792 10
Text and Coordinate
X_T and X_C
(x1,y1,x2,y2,w,h)
Input
Model
Output
Target Abstract:
Deep learning models are often successfully trained using gradient descent, ……..
……..
global optimality guarantee of gradient descent on a convolutional neural network with ReLU activations.
Important Image: Image x
Image Label
ICML2017-paper93
ICML2017-paper93-Figure5.1-1.png
ICML2017-paper93-Figure5.2-1.png
ICML2017-paper93-Figure5.3-1.png
ICML2017-paper93-Figure1.1-1.png
1 0 0 0
Image X_I
……
Image 1
Image n
Image Layout X_L
ICML2017-paper93
(x1,y1,x2,y2,w,h)
ICML2017-paper93-Figure5.1-1.png
58.559999999999995,67.67999999999999,520.3199999999999,174.23999999999998
ICML2017-paper93-Figure5.2-1.png
58.559999999999995,206.88,516.0,312.0
ICML2017-paper93-Figure5.3-1.png
58.559999999999995,339.84,516.0,445.44
ICML2017-paper93-Figure1.1-1.png
197.76,135.84,284.15999999999997,216.48

Figure 1. Input and output examples from the proposed multimodal-interactive network.

paper abstracts and selecting important images. This novel dataset integrates structural information, such as text coordinates and image layouts, overcoming the limitations of most existing summarization datasets, which typically include only text and images for training and validation. Future work will expand the dataset with more smart city document types (e.g., infrastructure topology maps, and public safety surveillance reports). Beyond its primary functionality, the proposed model can be extended to support text-image cross-modal retrieval applications [18–20]. In this context, researchers can utilize the generated abstract and selected image to effectively query related papers, facilitating easier access to relevant scientific literature [19,21]. We can leverage the power of retrieval in the smart city domain for other applications, such as locating accident scene images, automated visualization summaries for environmental monitoring systems, and decision support by quickly extracting information from municipal documents. This research establishes a bridge between academic exploration and urban intelligence [22], providing methodological foundations for deploying multimodal summarization in urban computing scenarios. To summarize, the main contributions of this work are as follows:

- We present a novel deep multimodal-interactive network that generates the abstract of a research paper while simultaneously selecting its most representative image. This approach facilitates a deeper understanding of the research content. By integrating both textual and visual modalities that convey complementary information at different semantic levels through a combination module, our multimodal learning framework enables researchers to access paper information beyond the constraints of text alone, thereby advancing scientific research.
- A structural information enhancement module that incorporates the spatial arrangement and layout of textual and visual elements is proposed. This module enhances the semantic understanding of the paper's structure by generating informative and meaningful summaries that include both the abstract and the most significant image.
- A new multimodal dataset that incorporates structural information is constructed to facilitate the evaluation process. This dataset overcomes the limitations of most existing summarization datasets, which typically only contain text and images for training and validation.
- Extensive experiments demonstrate the superior summarization capabilities of the proposed multimodal learning network, as evidenced by several key performance indicators. Additionally, the proposed model supports image-text cross-modal retrieval applications, showcasing its strong capabilities and significant potential in handling multimodal learning tasks, especially in the future smart city information management systems.

In the next section, we discuss some related works in the field of paper summarization and abstract generation. Subsequently, the proposed framework is detailed in Section 3, followed by a presentation of all experimental results in Section 4. Finally, in Section 5 and Section 6, we discuss future research directions and summarize this work.

2. Related Work

2.1. Document Summarization

Smart city data, including spatiotemporal traffic data [23] and cargo transportation information [24], often comes in text and image formats. Natural Language Processing (NLP) is a common method used to analyze this data. NLP technology can evaluate the shape, sound, and context of the collected information by leveraging computational resources. In the context of smart city applications—such as text and voice assistants in homes and businesses—NLP plays a crucial role in efficient data retrieval and analysis. It is also applied in medical data analysis, managing social networking platforms, language translation for improved communication, opinion mining, and Big Data Analytics (BDA) [25,26]. Among them, scientific document summarization has emerged as a significant research topic within the field of NLP [27]. This area encompasses various research directions, including dataset creation and multiple generation tasks such as abstract generation, literature review generation, figure caption generation, keyword extraction, and paper poster generation [28]. The development of summarization models is greatly influenced by the characteristics of the underlying datasets. While some models utilize textual content directly, others incorporate auxiliary information, such as text length and structural features [29], to aid in summary generation, including abstract creation. The combination of different datasets and tasks has established a comprehensive research framework in the domain of scientific document summarization. However, most of these methods primarily rely on text-based approaches, often overlooking the rich information embedded within the papers.

The intricate structure and extensive length of scientific documents create challenges in identifying the most representative components that effectively encapsulate the paper's information. To address this, researchers have investigated alternative modalities, particularly graphical abstracts, to create more concise summaries. The graphical abstract serves as the most critical visual element in our methodology, providing a succinct yet comprehensive representation of the paper's core concepts. Insights from related studies, such as those by Backer Johnsen et al. [30], emphasize the diversity of graphical abstracts in terms of expressive modes and clarity of arguments presented. Additionally, Ma et al. [31] highlighted the role of graphical abstracts in engaging readers and facilitating the dissemination of research findings to both domain experts and interdisciplinary scholars. Beyond textual descriptions, the visual modality offers unique advantages through the use of colors and line elements [32], thereby complementing the information conveyed by text. This synergy between textual and visual modalities underscores their complementary roles in effectively communicating scientific information [33].

2.2. Multimodal Summarization Techniques

Nowadays, multimodal summarization is rapidly developing, having many applications like reference text summarization [34] and meeting recordings summarization [35]. Different from the text-only summarization [36], multimodal summarization want to combine the feature from many modalities such as text and images, generating a meaningful summary which contain the multi-modal semantics. Multimodal summarization methodologies are roughly divided into two types: Multi-modal Summarization with Single-modal Output (MSSO) [37] and Multi-modal Summarization with Multi-modal Output (MSMO) [38].

MSSO focus on the quality of the generated text summary using multimodal data, which has only one type of output. A foundational contribution by Li et al. [39] introduced a specialized multimodal summarization framework that is trained on asynchronous documents, images, audio, and video. This framework employs four distinct criteria for sentence selection, thus enhancing the quality of the generated summaries. In a subsequent work, Li et al. [40] focused on the visual modality and proposed image filters, which are further refined through inner- and inter-modality attention mechanisms. These methods focus on critical image patches and text units to generate textual summaries, facilitating the extraction of useful information from both modalities.In parallel, several advancements have centered around the optimization of multimodal models through attention mechanisms. Xiao et al. [41] introduced a contribution network aimed at identifying the most informative image segments for multimodal summarization. This method efficiently integrates multimodal information, improving the semantic richness of the summaries. Building on this, Lu et al. [42] proposed an attention-based multimodal network that refines the synthesis of multi-modal inputs. Their approach enhances the semantic depth and logical coherence of the generated summaries by optimizing the interplay between modalities. In order to improve the quality of multimodal summarization, Li et al. [43] introduced a visual-guided modality regularization technique. This method directs the model's focus to the most crucial visual and textual elements within the source content, thereby improving sentence-level summarization. Yuan et al. [44] explored the trade-off between task-relevant and task-irrelevant visual information within an Information Bottleneck framework, aiming to optimize the extraction of meaningful content for task-specific summarization. In the realm of opinion summarization, Im et al. [45] presented the self-supervised multimodal opinion summarization model. This approach addresses the heterogeneity among input modalities, enabling more coherent and informative summaries from diverse sources. Song et al. [46] leveraged a vision-to-prompt methodology to generate product summaries. By converting visual information into semantic attribute prompts, this model harnesses the pre-trained language model's capabilities for generating coherent and contextually rich summaries. On a different front, Liu et al. [47] developed an annotation framework for multimodal dialogue summarization. This framework includes a video scene-cutting model and a set of standards for evaluating dialogue summaries, facilitating better integration of multimodal content. Zhang et al. [48] designed a multimodal generative adversarial network (GAN) that employs reinforcement learning techniques to generate concise and informative product titles. This model emphasizes the synthesis of visual and textual information, delivering more effective outputs in product summarization tasks.

Different from MSSO, MSMO fully utilized multimodal semantics through multimodal interaction networks to improve the quality of generated text summaries by combining collaborative tasks such as the most important selection task, which has several types of outputs like images and text. Early work in the domain includes Chen et al. [49], who introduced a multi-modal attentional mechanism to process images and text simultaneously. Their approach aimed to enhance text summarization by generating informative image summaries alongside textual content. Fu et al. [50] advanced this idea by proposing a model with bi-hop attention and an improved late fusion mechanism, which refined the generated summaries by extracting relevant images from video content. Their method produced both textual summaries and significant images simultaneously, addressing the challenges in summarizing articles and videos. In the same vein, Zhu et al. [51] developed a model designed for abstractive summarization, generating both textual summaries and the most relevant images for a given context. Their work laid the groundwork for more complex models that integrate multiple modalities in summarization tasks. This line of research was further expanded by Zhu et al. [52], who introduced a multi-modal objective function that incorporates both image and text references during training. The combined loss function facilitated the generation of more coherent multimodal summaries by jointly considering both tasks in the model's learning process. Tan et al. [53] contributed to the field by utilizing the power of large language models (LLMs) while effectively integrating multimodal information within a unified framework. Their approach not only generated text summaries but also selected a graphical abstract, thus enhancing the ability to summarize complex multi-modal content. Similarly, Zhu et al. [54] presented a unified framework for multi-modal summarization that integrated various tasks into a single system. They also introduced three unsupervised multi-modal ranking models, which could be tailored to different tasks or scenarios based on specific requirements. Zhang et al. [55] proposed a unified multi-modal summarization framework based on an encoder-decoder multitask architecture built on BART. This framework was capable of simultaneously generating text summaries and selecting images, enabling more effective multimodal summarization. In a subsequent study, Zhang et al. [56] further enhanced inter-modality interaction by introducing a multimodal visual graph learning method. This method helped capture both structural and content information, facilitating stronger interactions between modalities. Zhuang et al. [38] addressed the evaluation aspect of multi-modal summarization by designing mLLM-EVAL, a reference-free evaluation method utilizing multimodal LLMs. This model aimed to improve the accuracy and reliability of evaluating multi-modal summaries without relying on manually annotated references. Mukherjee et al. [57] proposed a multi-task learning approach that simultaneously tackled two tasks: classifying in-article images as either "on-topic" or "off-topic" and generating a multimodal summary. The classification task served as an auxiliary task, helping the model to extract combined features from text and images for more effective summary generation.

Existing datasets in multimodal summarization field lack the annotation of image labels and the simultaneous acquisition of coordinates to get the structural information, making the most important image selection task difficult to accomplish [58]. The proposed method learns the correlations between images and text accompanied by structural information like coordinate of text and layout of image. And we create a new dataset to provide more perspectives on multimodal learning to generate scientific paper abstract.

3. Methodology

3.1. Overall Framework

The proposed learning framework leverages multimodal data to simultaneously generate paper abstracts and identify the most relevant image. The architecture incorporates multimodal information by augmenting both textual and visual feature representations through different modules. To effectively integrate these complementary modalities, the model employs advanced fusion mechanisms that exploit cross-modal correlations to enhance the performance of both tasks. This model architecture consists of three primary components, as illustrated in Figure 2. Overall, the proposed deep model involves three key components: (1) a structural information enhancement module that incorporates structural information (e.g., coordinate of text and layout of image) to extracted features from both text and images; (2) a combination module that establishes correlations between textual and visual content to fuse them; and (3) an output module that optimizes the model for both abstract generation and image selection tasks. These modules integrate features from multiple levels, including text, images, coordinates, and layout information, while accounting for cross-modal interactions.

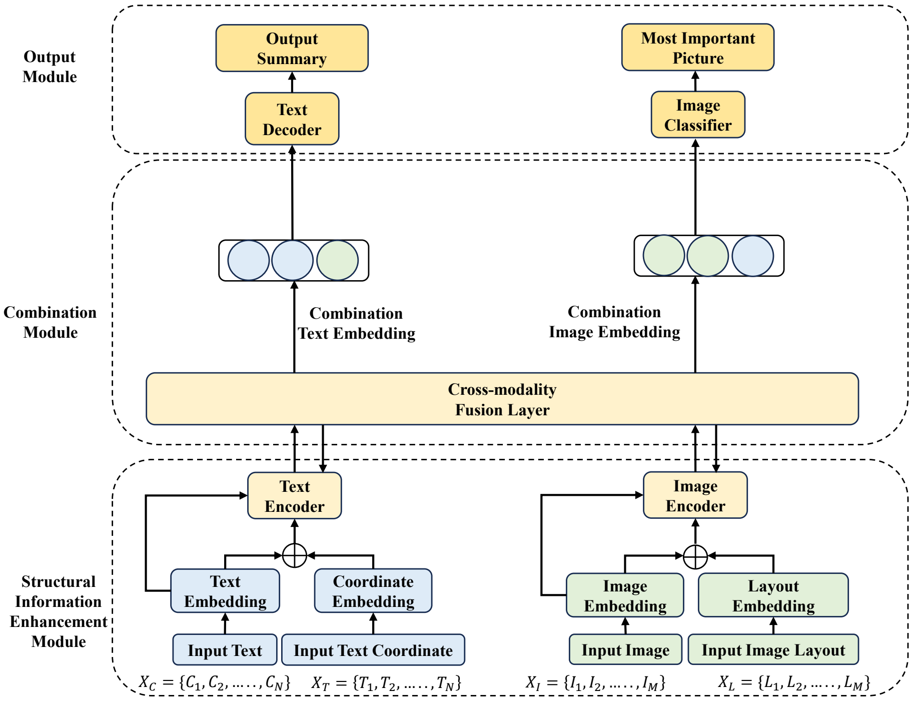
Output Module
Output Summary
Text Decoder
Most Important Picture
Image Classifier
Combination Module
Combination Text Embedding
Combination Image Embedding
Cross-modality Fusion Layer
Text Encoder
Image Encoder
Structural Information Enhancement Module
Text Embedding
Coordinate Embedding
Image Embedding
Layout Embedding
Input Text
Input Text Coordinate
Input Image
Input Image Layout
$X_C = \{C_1, C_2, \ldots, C_N\}$
$X_T = \{T_1, T_2, \ldots, T_N\}$
$X_I = \{I_1, I_2, \ldots, I_M\}$
$X_L = \{L_1, L_2, \ldots, L_M\}$

Figure 2. The overall framework of our model.

Our model takes as input the textual content $X_T = (T_1, \ldots, T_N)$, text coordinates $X_C = (C_1, \ldots, C_N)$, paper images $X_I = (I_1, \ldots, I_M)$, and image layout information $X_L = (L_1, \ldots, L_M)$ of a scientific paper. The goal is to generate a multimodal summary consisting of an abstract $Y_t = (y_1, y_2, \ldots, y_t)$ and the most important image $Y_i = I_N$. The model is defined by a set of trainable parameters θ and aims to solve the following optimization problem:

$$argmax_\theta \mathcal{L}(Y_t, Y_i \mid X_T, X_C, X_I, X_L; \theta) \quad (1)$$

where $\mathcal{L}$ represents the loss function to be minimized in Equation (1).

3.2. Structural Information Enhancement Module

To effectively incorporate the structural information of images and text into the feature representation, we propose a structural information enhancement module. This component processes the image and text components separately, as illustrated in Figure 3.

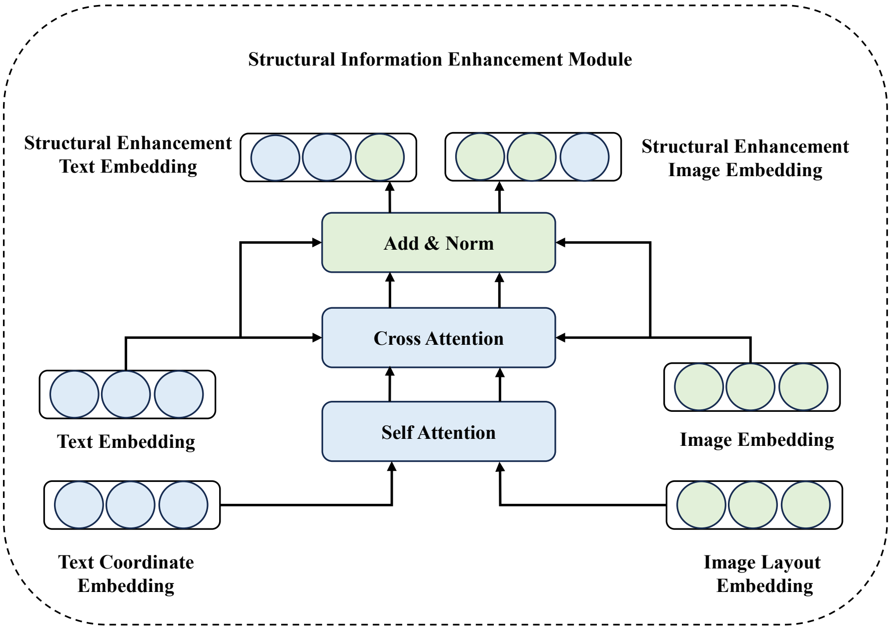
Structural Information Enhancement Module
Structural Enhancement Text Embedding
Structural Enhancement Image Embedding
Add & Norm
Cross Attention
Self Attention
Text Embedding
Image Embedding
Text Coordinate Embedding
Image Layout Embedding

Figure 3. The structural information enhancement module.

3.2.1. Structural Embedding Layer

Given a collection of image layouts $X_L = \{L_1, L_2, \ldots, L_M\}$ and text coordinates $X_C = \{C_1, C_2, \ldots, C_N\}$, we employ these to enhance the image and text embeddings by incorporating structural information. Specifically, the structural embedding layer is trained to generate layout embeddings and coordinate embeddings, which are subsequently integrated into the respective image and text embeddings. For image embedding enhancement, we define distinct embedding functions for each layout dimension $(X_1, Y_1, X_2, Y_2, W, H)$ and aggregate these embeddings to compute the overall position embedding as follows (Equation (2) and Equation (3)):

$$LayoutEmbedding(X_L) = E(X_1) + E(Y_1) + E(X_2) + E(Y_2) + E(W) + E(H) \tag{2}$$

$$X_L^a = LayoutEmbedding(X_L) \tag{3}$$

where $E(X_1), E(Y_1), E(X_2), E(Y_2), E(W)$, and $E(H)$ are trainable embedding functions for each layout dimension. The resulting embedding, denoted as X_L^a, is the summation of these individual embeddings.

Similarly, for text embedding enhancement, we define separate position embeddings for each coordinate dimension $(X_1, Y_1, X_2, Y_2, W, H)$ and combine them to form the overall position embedding (Equation (4) and Equation (5)):

$$CoordEmbedding(X_C) = E(X_1) + E(Y_1) + E(X_2) + E(Y_2) + E(W) + E(H) \tag{4}$$

$$X_C^a = CoordEmbedding(X_C) \tag{5}$$

where X_C^a represents the aggregated embedding derived from these coordinate-specific embeddings.

3.2.2. Image Enhancement

Given a set of paper images $X_I = \{I_1, I_2, \ldots, I_M\}$, we utilize ResNet-152 [59] to extract visual features, thereby obtaining the image embedding X_I^a. The feature extraction process can be expressed as Equation (6):

$$X_I^a = ResNet152(X_I) \tag{6}$$

In addition, we have derived a layout embedding X_L^a from the image layout as described earlier. We use a standard attention mechanism, with the Equation (7). When the query, key, and value all come from the same sequence, it is referred to as self-attention. When the query comes from one sequence and the key and value come from another sequence, it is referred to as cross-attention. To enhance the image embedding, we first apply a self-attention mechanism (Equation (8)) to strengthen the layout information, followed by a cross-attention mechanism (Equation (9)) to fuse the image and layout features. The operations are defined as:

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d}}\right)V \tag{7}$$

$$X_L^b = SelfAttention(X_L^a, X_L^a, X_L^a) \tag{8}$$

$$X_L^c = CrossAttention(X_I^a, X_L^b, X_L^b) \tag{9}$$

Here, X_L^b represents the output of the self-attention layer, while X_L^c denotes the output of the cross-attention layer.

The final enhanced image embedding is obtained by integrating the layout-enhanced features into the original image embedding in Equation (10):

$$X_I^c = X_I^a + W_1 * X_L^c \tag{10}$$

$$X_I^d = AddNorm(FFN(AddNorm(X_I^c))) \tag{11}$$

where W_1 is a trainable weight, and X_I^d (Equation (11)) is the result of applying a feed-forward network with residual connections and normalization. Notably, all layers except the feature extraction component are retrained to adapt to the specific task.

3.2.3. Text Enhancement

Given a set of paper text $X_T = \{T_1, T_2, \ldots, T_N\}$, we leverage the BART model [60] to extract text embeddings X_T^a through its embedding layer. The process can be expressed as Equation (12):

$$X_T^a = BART_{embeddinglayer}(X_T) \tag{12}$$

We also derive a coordinate embedding X_C^a from the text coordinates, as described earlier. To enhance the text embedding, we first apply a self-attention mechanism (Equation (13)) to emphasize the coordinate information and then employ a cross-attention mechanism (Equation (14)) to combine the text and coordinate features. The operations are defined as:

$$X_C^b = SelfAttention(X_C^a, X_C^a, X_C^a) \tag{13}$$

$$X_C^c = CrossAttention(X_T^a, X_C^b, X_C^b) \tag{14}$$

Here, X_C^b represents the output of the self-attention layer, while X_C^c denotes the output of the cross-attention layer.

The final enhanced text embedding is obtained by integrating the coordinate-enhanced features into the original text embedding in Equation (15):

$$X_T^c = X_T^a + W_2 * X_C^c \tag{15}$$

$$X_T^d = AddNorm(FFN(AddNorm(X_T^c))) \tag{16}$$

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where W_2 is a trainable weight, and X_T^d (Equation (16)) is the result of applying a feed-forward network with residual connections and normalization. Unlike the image enhancement process, we utilize pre-trained weights for layers overlapping with the original BART model to improve performance.

3.3. Combination Module

The integration of visual and textual information is crucial for capturing comprehensive and diverse representations of scientific papers. Specifically, the most important image should encapsulate the primary topic of the paper, while the abstract contains key information. Therefore, text and image modalities can complement each other, providing a more holistic understanding. This module is designed to fuse the information between images and text, as illustrated in Figure 4.

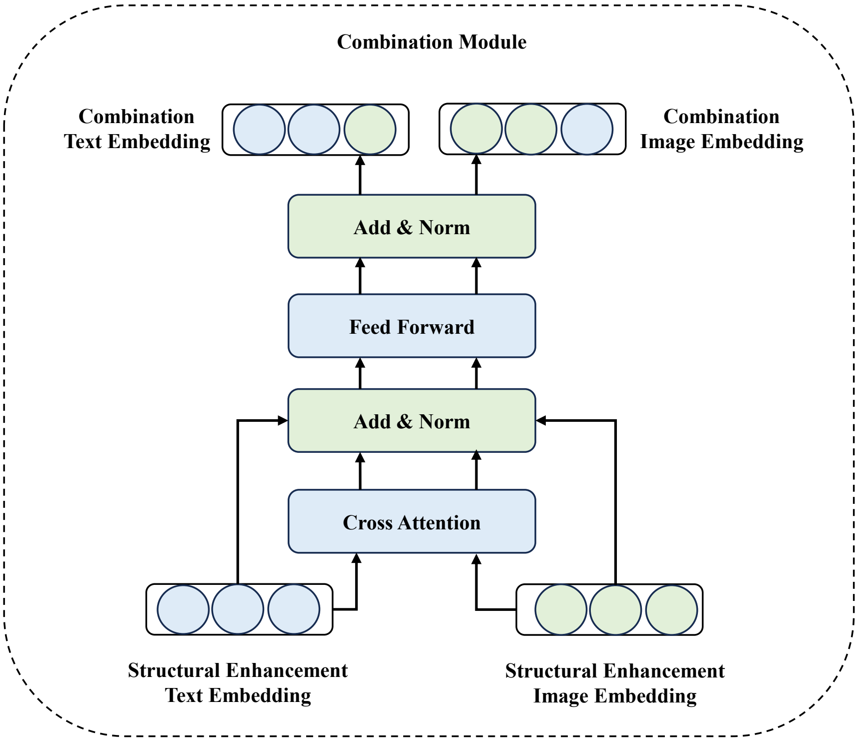

Combination Module
Combination Text Embedding
Combination Image Embedding
Add & Norm
Feed Forward
Add & Norm
Cross Attention
Structural Enhancement Text Embedding
Structural Enhancement Image Embedding

Figure 4. The combination module.

3.3.1. Image-to-Text Combination

To integrate image and text features, we employ a two-stage process that begins with compressing and transforming the text features before combining them with the image features. Specifically, the text embedding X_T^d is compressed into a vector using an averaging operation and then expanded back into a matrix (Equation (17)). This matrix is transformed using a trainable weight matrix W_3 (Equation (18)) and passed through a linear layer to generate a new feature representation (Equation (19)). Subsequently, a cross-attention mechanism is applied to combine these transformed text features with the image features X_I^d (Equation (20)), which already contain structural information. The final output is obtained by weighting and summing the enhanced features (Equation (21)). The image-text combination process is implemented as follows:

$$M_T^a = Repeat(Mean(X_T^d)) \tag{17}$$

$$M_T^b = M_T^a * W_3 \tag{18}$$

$$M_T^c = Linear(M_T^b) \tag{19}$$

$$M_T^d = CrossAttention(X_I^d, M_T^c, M_T^c) \tag{20}$$

$$M_{I-T}^a = X_I^d + W_4 * M_T^d \tag{21}$$

$$M_{I-T}^b = AddNorm(FFN(AddNorm(M_{I-T}^a))) \tag{22}$$

Here, M_T^a (Equation (22)) represents the compressed and expanded text embedding, M_T^b is the transformed text feature, and M_T^c is the output of the linear transformation. The cross-attention mechanism produces M_T^d, which is then combined with the image features X_I^d to form M_{I-T}^a. Finally, M_{I-T}^b is obtained through a feed-forward network with residual connections and normalization.

3.3.2. Text-to-Image Combination

In parallel, we develop a complementary strategy to integrate image and text features in the reverse direction, ensuring a bidirectional flow of information. The image embedding X_I^d is first compressed into a vector using an averaging operation and then expanded back into a matrix (Equation (23)). This matrix is transformed using a trainable weight matrix W_5 (Equation (24)) and passed through a linear layer to generate a new feature representation (Equation (25)). Subsequently, a cross-attention mechanism (Equation (26)) is applied to combine these transformed image features with the text features X_T^d, which already contain structural information. The final output is obtained by weighting and summing the enhanced features (Equation (27)). The text-image combination process is implemented as follows:

$$M_I^a = Repeat(Mean(X_I^d)) \tag{23}$$

$$M_I^b = M_I^a * W_5 \tag{24}$$

$$M_I^c = Linear(M_I^b) \tag{25}$$

$$M_I^d = CrossAttention(X_T^d, M_I^c, M_I^c) \tag{26}$$

$$M_{T-I}^a = X_T^d + W_4 * M_I^d \tag{27}$$

$$M_{T-I}^b = AddNorm(FFN(AddNorm(M_{T-I}^a))) \tag{28}$$

Here, M_I^a (Equation (28)) represents the compressed and expanded image embedding, M_I^b is the transformed image feature, and M_I^c is the output of the linear transformation. The cross-attention mechanism produces M_I^d, which is then combined with the text features X_T^d to form M_{T-I}^a. Finally, M_{T-I}^b is obtained through a feed-forward network with residual connections and normalization.

3.4. Output Module

To maximize the utilization of multimodal information, we developed the output module capable of concurrently generating the paper abstract and selecting the most representative image. This module leverages a pre-trained BART decoder to derive decoded text features, which are subsequently employed for abstract generation. Simultaneously, the most significant image is identified using the encoded visual information, enabling the two modalities to complement each other and enhance task performance. For training, we employ negative log-likelihood loss for abstract generation and cross-entropy loss for image selection. A multi-task learning framework [61] is implemented to train both tasks in parallel, as illustrated in Figure 5.

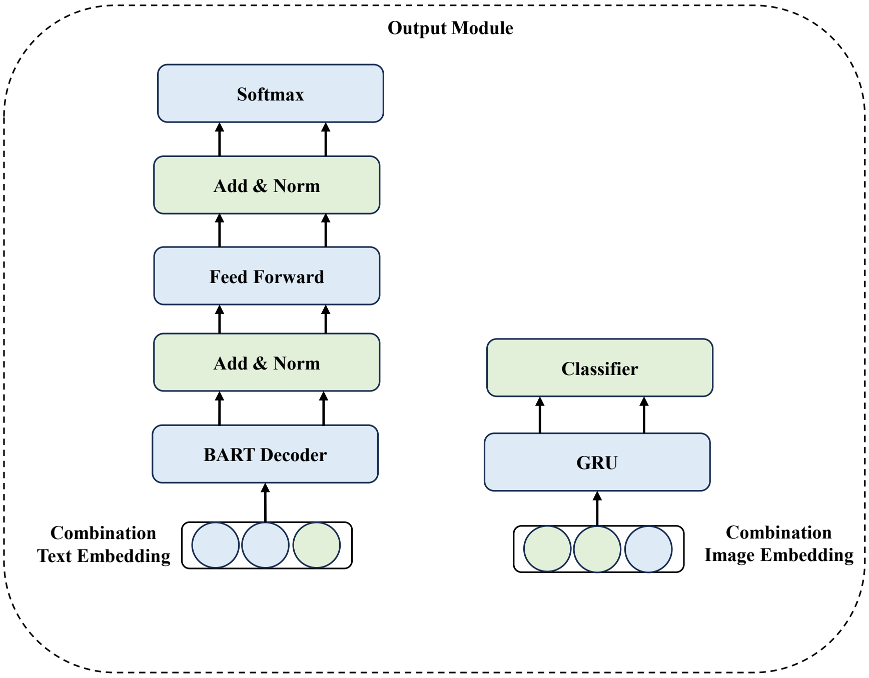


Figure 5. The output module.

3.4.1. Paper Abstract Generation

The abstract generation task aims to utilize the integrated text-image feature M^b_{T-I} to produce the paper's abstract. This is achieved by feeding the fused text-image embedding into a pre-trained BART decoder [60] to extract decoded embeddings, which are then used for abstract generation. The decoding process can be mathematically represented as Equation (29):

$$M^c_{T-I} = BART_{decoder}(M^b_{T-I}) \tag{29}$$

Here, M^c_{T-I} denotes the decoded embeddings.

Subsequently, these embeddings undergo a series of transformations to generate token probabilities (Equation (30) and Equation (31)):

$$M^d_{T-I} = AddNorm(FFN(AddNorm(M^c_{T-I}))) \tag{30}$$

$$P_t = Softmax(M^d_{T-I}) \tag{31}$$

In these equations, M^d_{T-I} represents the output after applying a feed-forward network, residual connections, and normalization. P_t signifies the probability distribution over tokens.

The loss function is defined as Equation (32):

$$\mathcal{L}^{Text}_{\theta} = \sum_t \log P_t(y_t) \tag{32}$$

This negative log-likelihood loss is minimized during training to refine the model's ability to generate tokens closely resembling the target sequence y_t.

3.4.2. The Most Important Image Selection

For the image selection task, we recognize the importance of both visual and textual information in identifying the most representative image. This task is performed using the previously derived image-text embedding M^b_{I-T}. The process involves transforming the embedding through a linear layer (Equation (33)) to match the dimensionality required by a GRU [62] model (Equation (34)), which captures the temporal relationships among images. The resulting features are subsequently reduced to a 1D tensor (Equation (35) and Equation (36)), enabling the selection of the most crucial image for each paper. The process can be formalized as:

$$M^c_{I-T} = Linear(M^b_{I-T}) \tag{33}$$

$$M^d_{I-T} = GRU(M^c_{I-T}) \tag{34}$$

$$Classifier_{Image}(M^e_{I-T}) = Linear_{1-D}(M^e_{I-T}) \tag{35}$$

$$y_I = Classifier_{Image}(M^e_{I-T}) \tag{36}$$

In this formulation, M^c_{I-T} represents the output of the linear transformation layer, M^d_{I-T} is the GRU output, and y_I denotes the computed score for each image.

The loss function is defined as Equation (37):

$$\mathcal{L}^{Image}_\theta = -\frac{1}{N}\sum_{i=1}^{N}[\widehat{y_I}\log(y_I) + (1-\widehat{y_I})\log(1-y_I)] \tag{37}$$

This cross-entropy loss measures the discrepancy between the predicted scores y_I and the ground truth scores $\widehat{y_I}$. The selected image not only serves as the most representative visual summary but also aligns with the textual content.

3.5. Total Loss Function

The proposed model enables joint training of the abstract generation and image selection tasks. Both tasks are optimized simultaneously through the combined loss function in Equation (38):

$$\mathcal{L}^{Total}_\theta = a\mathcal{L}^{Image}_\theta + b\mathcal{L}^{Text}_\theta \tag{38}$$

Here, a and b are learnable parameters that balance the contributions of the two tasks during training.

4. Experiment and Result

4.1. Dataset Detail

Existing summarization datasets typically contain either text or images for training and validation. To address this limitation, we developed a novel dataset that incorporates both text and images, along with structural information such as text coordinates and image layouts. Our dataset creation methodology draws inspiration from recent advancements in the field. Below, we outline the dataset construction process.

First, we sourced a diverse collection of scientific publications from reputable open-access repositories, including top-tier conferences such as NIPS, ACL, and ICML. To extract images and their associated structural information, we employed PDFigCapX [63], a robust tool for parsing academic paper's content. After collecting the original image data, we implemented a labeling process. Following the methodology proposed by Tan et al. [53], we identified the most significant image in each paper based on specific keywords in the captions, such as "overview," "overall," and "model architecture." This step ensured that the selected images were representative of the paper's core content. The output included figures, their captions, and layout, as illustrated in Figure 6.

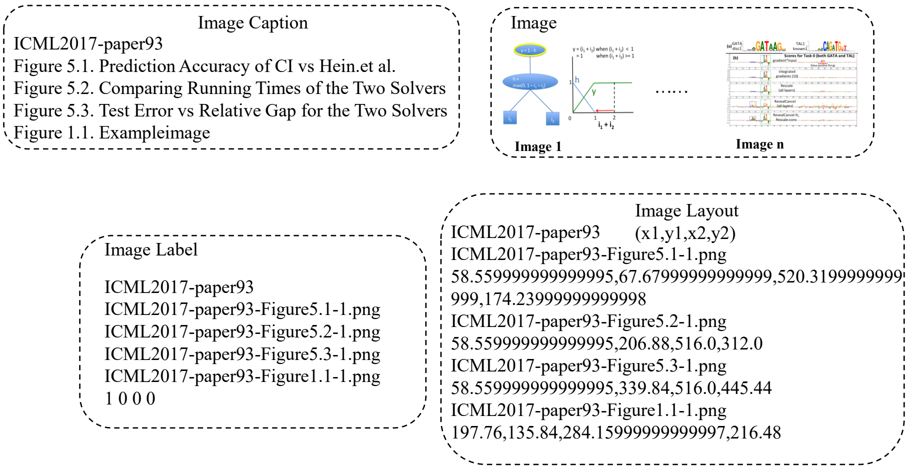


Image Caption
ICML2017-paper93
Figure 5.1. Prediction Accuracy of CI vs Hein.et al.
Figure 5.2. Comparing Running Times of the Two Solvers
Figure 5.3. Test Error vs Relative Gap for the Two Solvers
Figure 1.1. Exampleimage

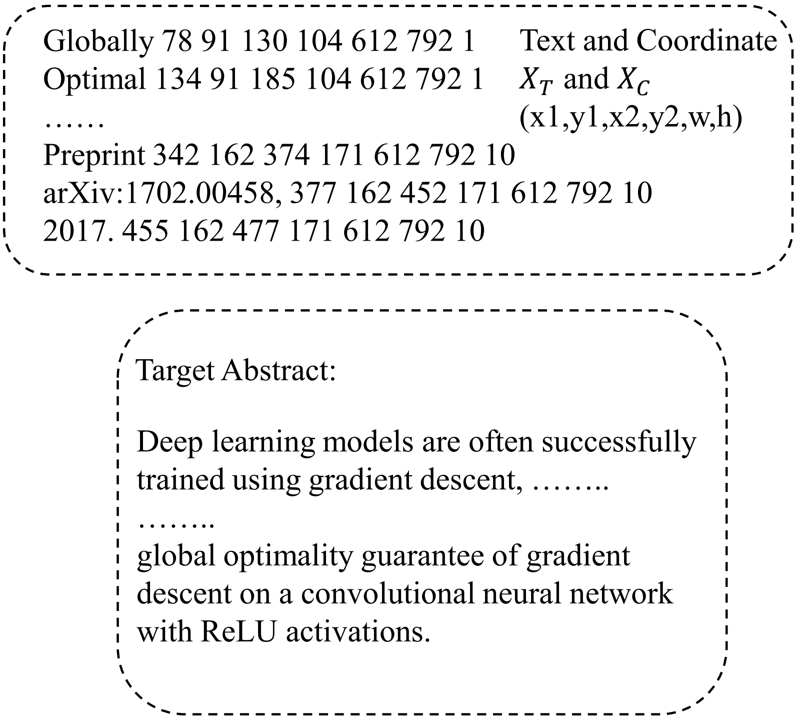
Image Label

ICML2017-paper93
ICML2017-paper93-Figure5.1-1.png
ICML2017-paper93-Figure5.2-1.png
ICML2017-paper93-Figure5.3-1.png
ICML2017-paper93-Figure1.1-1.png
1 0 0 0

Image Layout
ICML2017-paper93 (x1,y1,x2,y2)
ICML2017-paper93-Figure5.1-1.png
58.559999999999995,67.67999999999999,520.3199999999999,174.23999999999998
ICML2017-paper93-Figure5.2-1.png
58.559999999999995,206.88,516.0,312.0
ICML2017-paper93-Figure5.3-1.png
58.559999999999995,339.84,516.0,445.44
ICML2017-paper93-Figure1.1-1.png
197.76,135.84,284.15999999999997,216.48

Figure 6. The image part of the dataset.

Additionally, we adopted the dataset creation method outlined by [29] to extract token-level information, including token coordinates (x1, y1, x2, y2, w, h), as demonstrated in Figure 7.



Globally 78 91 130 104 612 792 1
Optimal 134 91 185 104 612 792 1
……
Preprint 342 162 374 171 612 792 10
arXiv:1702.00458, 377 162 452 171 612 792 10
2017. 455 162 477 171 612 792 10

Text and Coordinate
X_T and X_C
(x1,y1,x2,y2,w,h)

Target Abstract:

Deep learning models are often successfully trained using gradient descent, ……..
……..
global optimality guarantee of gradient descent on a convolutional neural network with ReLU activations.

Figure 7. The text part of the dataset.

Table 1 provides a detailed overview of our dataset, including the number of papers, images, and associated metadata.

4.2. Implementation Detail

Data Preprocessing: We utilized the BART tokenizer [64] to tokenize all text content from our scientific papers.

Model Architecture: Our model's text embedding matrix was initialized using the pre-trained BART model, which features a vocabulary size of 50,264 and an embedding dimension of 1,024. Both

Table 1. Dataset statistics.

	Train	Valid	Test
Num. Papers	615	65	163
Avg. Num. Words in papers	6784.90	7088.75	6836.77
Avg. Num. Words in Summary	124.30	128.78	125.64
Avg. Num. Image in Papers	6.69	6.85	6.74
Max. Num. Image in Papers	19	17	25
Min. Num. Image in Papers	1	1	1
Max. Num. Words in Papers	14084	12746	13119
Min. Num. Words in Papers	2854	3166	3085
Max. Num. Words in Summary	285	216	285
Min. Num. Words in Summary	40	56	32

the source text (including paper content and summaries) and the target text shared the same vocabulary. For image processing, we employed the ResNet-152 encoder to extract visual features, resulting in a 2048-dimensional representation for each image.

Training: The model was trained with the following hyperparameters: batch size of 2, learning rate of 0.00001, and the Adam optimizer [65]. All experiments were conducted on an NVIDIA RTX 4090 GPU.

Testing: During evaluation, we set the maximum decoding length to 256 tokens. Other parameters, such as beam size and length penalty, were kept at their default values.

Evaluation Metrics: We employed the ROUGE [66] metric to assess summary quality, considering dimensions such as Rouge-1, Rouge-2, Rouge-L and RougeLSum. Additionally, we measured the quality of image selection using Top-K Accuracy [67].

4.3. Baseline Model

To assess the performance of our proposed model, we conducted a comprehensive comparison against various baseline approaches, encompassing both extractive and abstractive summarization methods.

Extractive Models: Extractive summarization techniques [68] generate summaries by selecting the most relevant sentences or phrases directly from the source document. These methods are valued for their simplicity and efficiency, as they preserve the original meaning of the text. For this study, we evaluated several prominent extractive models:

- **Lead-3:** Lead-3 is a simple yet widely used baseline model that selects the first three sentences of a document as the summary. It is based on the assumption that the most important information is often located at the beginning of a text.
- **SumBasic:** SumBasic is a sentence extraction algorithm that relies on basic features such as sentence length, position, and the presence of capital words. It assigns scores to sentences based on these features and selects the top-ranked sentences to form the summary.
- **TF-IDF:** TF-IDF (Term Frequency-Inverse Document Frequency) identifies important words in a document by calculating their frequency and their rarity across a corpus. The model then extracts sentences containing these high-weight words to form the summary.
- **TextRank:** TextRank treats sentences as nodes in a graph and computes their importance based on their similarity to other sentences. It iteratively ranks sentences and selects the top-ranked ones to generate the summary.
- **LexRank:** LexRank is an improved version of TextRank that uses a more efficient algorithm to compute sentence importance. It also focuses on maintaining semantic similarity between sentences to produce coherent summaries.

Abstractive Models: Abstractive methods [69] leverage semantic understanding to generate summaries by rephrasing the source content. These models produce more natural and human-like outputs compared to extractive approaches. The abstractive models evaluated in this study include:

- **T5:** T5 is a versatile and powerful model designed for various text-based tasks, including text summarization. It leverages a pre-training approach on a wide range of text-to-text tasks and has shown remarkable performance in generating concise and coherent summaries.
- **MBart:** MBart is a multilingual pre-trained model optimized for text summarization and machine translation. Its ability to handle multiple languages makes it particularly suitable for cross-lingual summarization tasks, providing robust performance across diverse datasets.
- **LED:** LED is a model specifically designed for document summarization, focusing on generating informative and concise summaries. It employs a lightweight approach to editing and compression, making it efficient for handling long texts.
- **Pegasus:** Pegasus is a model developed for abstractive summarization tasks. It utilizes a novel pre-training strategy that incorporates extracted summarization guidance, enabling it to generate high-quality, human-like summaries.
- **DistilBART:** DistilBART is a lightweight and efficient variant of the BART model, designed to reduce computational resources while maintaining high performance. It is particularly useful for scenarios where resource constraints are a concern.

4.4. Comparison Result

To evaluate the effectiveness of our proposed model, we conducted a comprehensive comparison with baseline models, which can be categorized into extractive and abstractive models. Notably, our abstractive models underwent pre-training on the widely-used CNN Daily Mail dataset prior to fine-tuning on our dataset. As demonstrated in Table 2, our model achieves superior performance across all metrics. Our findings reveal three key insights. First, abstractive models consistently outperform extractive models, underscoring the importance of content generation over mere information extraction for effective summarization. Second, our model demonstrates the best performance among all abstractive approaches, likely due to its unique architecture that integrates both multimodal data and multi-task learning. The incorporation of multiple modalities, combined with structural information, enables our model to effectively capture the interdependencies between images and text. Third, our experiments indicate that the image selection task, when conducted in tandem with the primary abstract generation task, enhances the model's ability to identify salient images while producing high-quality summaries. This dual capability contributes significantly to the model's overall performance.

Table 2. The performance of comparative models on the dataset.

	Model	Rouge1	Rouge2	RougeL	RougeLSum
Extractive Models	Lead3[70]	24.9487	6.3754	13.6919	13.6954
	Sumbasic[71]	22.9243	3.9666	11.3793	11.3944
	TextRrank [72]	30.9347	6.2924	17.0652	17.0658
	LexRank[73]	29.6314	5.8603	16.184	16.2027
	TF-IDF[74]	24.8868	5.0350	11.4188	11.4339
Abstractive Models	T5 [75]	30.4562	7.5950	19.0483	19.0540
	Mbart[76]	37.3201	9.0104	19.8601	19.8400
	Led[77]	42.1852	12.3763	20.3438	20.3380
	Pegasus[78]	43.6267	14.6201	24.4578	24.4086
	DistilBart [79]	38.9486	10.9574	21.0662	21.0610
	Proposed	**46.5545**	**16.1336**	**24.9548**	**24.9227**

4.5. Visualization Result

Table 3 presents the output summaries generated by different models. For reference, the original abstract is included in the top line of Table 3. To assess the quality of the generated summaries, we employ human evaluation. In Table 3, we use blue labels to highlight segments that share the same meaning as the original summary, red labels to denote segments that are semantically irrelevant to the original summary, and orange labels to identify redundant parts that have been generated multiple

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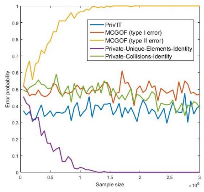
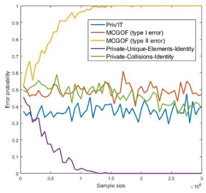
Table 3. The comparison of output between the proposed network and other models.

Model	Output
Ground Truth	We study the fundamental problems of identity and equivalence testing over a discrete population from random samples. Our goal is to develop efficient testers while guaranteeing differential privacy to the individuals of the population. We provide sample-efficient differentially private testers for these problems. Our theoretical results significantly improve over the best known algorithms for identity testing, and are the first results for private equivalence testing. The conceptual message of our work is that there exist private hypothesis testers that are nearly as sample-efficient as their non-private counterparts. We perform an experimental evaluation of our algorithms on synthetic data. Our experiments illustrate that our private testers achieve small type I and type II errors with sample size sublinear in the domain size of the underlying distributions. 
T5	We study the general problem of differential privacy in the setting of differential privacy. We use a simple generic method to test the identity and equivalence of Discrete Distributions to test the identity and equivalence of discrete distributions. We use a simple generic method to test the identity and equivalence of Discrete Distributions. We use a simple generic method to test the identity and equivalence of Discrete Distributions.
MBart	We present a novel algorithm for differential and Equival Testing of Discrete Distributions (DDH) that exploits the problem of differential privacy in a large network of datasets. We demonstrate that this method achieves better results than private-private data distributions, but that does not achieve the best results in the small domain of the dataset. Our experiments show that the privacy of the domains over the large distributions can be achieved in a small range of properties, including whether a distribution is uniform or a known distribution.
Led	Differently Private Identity and Equivalence Testing of Discrete Distributions (Dwork & Roth, 2014) is a rich and active area of study, in which techniques have been developed to obtain statistical tests that can be applied to different data analysis tasks. In this paper, we show that we can achieve differential privacy with only a small increase in the sample complexity compared to the non-private case. Our results significantly improve over the best known algorithms for identity testing and are the first results for private equivalence testing. We also demonstrate that our approach improves on existing methods by achieving small type I and type II errors with a sublinear number of samples when the domain size is large. The main conceptual message of our work is that we attain differential privacy without compromising the privacy of the individuals in the dataset.
Pegasus	We consider the problem of designing sample-efficient algorithms for testing the identity and equivalence of discrete distributions over large discrete domains. In particular, we focus on the sublinear regime, when the number of samples available is sublinear in the domain size of the underlying distribution(s). We develop two private equivalence testing algorithms for the problem: one for identity testing, and one for equivalence testing. Our theoretical results significantly improve over the best known algorithms for this problem, and are the first results for private equivalency testing.
DistilBart	We consider the problem of designing sample-efficient algo-rithms to understand the distribution over large discrete domains. In this paper we introduce a new approach to this problem, which is based on the number of samples when the domain size is large. Our experiments show that our method is competitive with the state-of-the-art approaches for this problem. We show that it outperforms the state of the art by a small increase in the sample complexity compared to the non-private case. We also show that the proposed method outperforms existing approaches.
Proposed	We consider the problem of designing sample-efficient algorithms to understand properties of distributions over large discrete domains. In this paper, we study the problem in the setting of differential privacy, where the number of samples available is sublinear in the domain size of the underlying distribution(s) We develop two algorithms that achieve differential privacy with only a small increase in the sample complexity compared to the non-private setting. We show that our private identity and private equivalence testing algorithms can be achieved essentially for free, i.e., with a very mild increase in sample complexity. Our theoretical results significantly improve over the best known algorithms for identity testing, and are the first results for private equalization testing. Our experimental evaluation illustrates that our testers achieve small type I and type II errors with a sublinear number ofamples when the domain is large. 

doi:10.20944/preprints202503.2167.v1

times. Our findings indicate that the results of the human evaluation align closely with the trends observed in the ROUGE scores. Summaries that achieve higher ROUGE scores tend to be more precise and semantically accurate. As shown in Table 3, the integration of image features in our model enables the generation of summaries that are not only more accurate but also more meaningful, selecting the most relevant image to represent the content.

4.6. Ablation Study

To investigate the impact of different components on model performance, we conducted ablation studies on two modules by modifying the full model architecture. In the first study, we compared two configurations of the Combination Module (CM): one that included the CM and one that did not (W/o CM). In the second study focusing on the Structural Information Enhancement Module (SEM), we similarly compared configurations with the SEM and without it (W/o SEM). Our experiments targeted three tasks: the most important image selection task (I), the scientific paper abstract generation task (T), and a joint task that combined both (I+T). The results, shown in Tables 4 and 5, indicate that incorporating both the CM and SEM significantly improves performance across all tasks. With the integration of these modules, the model demonstrates enhanced capabilities in both image selection and abstract generation, highlighting the effective fusion of visual and textual information. Conversely, when only a single module is utilized (W/o CM or SEM), the performance declines, emphasizing the importance of multimodal data fusion. Notably, in the joint task (I+T), our model achieves slightly higher ROUGE scores compared to the single-modality tasks, reinforcing the significance of the image selection task in enhancing overall model performance.

Table 4. The ablation study of the combination module on the dataset.

Type	Task	Rouge1	Rouge2	RougeL	RougeLSum	Top-1	Top-2
W/o CM	I	-	-	-	-	85.28%	94.48%
	T	45.8707	15.4908	24.7259	24.6456	-	-
	I+T	46.0182	15.5612	24.7648	24.7674	85.89%	95.09%
With CM	I	-	-	-	-	86.50%	93.87%
	T	46.2762	15.8483	24.7441	24.7765	-	-
	I+T(ours)	**46.5545**	**16.1336**	**24.9548**	**24.9227**	**87.12%**	**95.71%**

Table 5. The ablation study of the structural information enhancement module on the dataset.

Type	Task	Rouge1	Rouge2	RougeL	RougeLSum	Top-1	Top-2
W/o SEM	I	-	-	-	-	84.66%	93.87%
	T	45.8372	15.6966	24.5167	24.5102	-	-
	I+T	46.2108	15.8813	24.7682	24.8199	85.28%	95.09%
With SEM	I	-	-	-	-	86.50%	93.87%
	T	46.2762	15.8483	24.7441	24.7765	-	-
	I+T(ours)	**46.5545**	**16.1336**	**24.9548**	**24.9227**	**87.12%**	**95.71%**

4.7. Cross-Modal Retrieval Application

We further apply our model to cross-modal retrieval tasks in the forms of image-to-text and text-to-image. This application holds significant value in the realm of information retrieval, as it can greatly enhance the efficiency with which researchers retrieve relevant scientific literature. In the context of text-to-image retrieval, we utilize the abstract of a paper to compute its similarity with images associated with the paper, identifying the most relevant image and verifying whether it corresponds to the same article. Conversely, in image-to-text retrieval, we assess the similarity between the paper's image and its abstract, aiming to retrieve the most pertinent abstract and determine if it pertains to the same paper. To evaluate the effectiveness of the retrieval process, we employ the Mean Average Precision at top-K (MAP@K) metric [19,21], which is commonly used for evaluating performance in both text-to-image and image-to-text retrieval tasks. MAP offers a holistic evaluation of a retrieval

doi:10.20944/preprints202503.2167.v1

Table 6. The retrieval performance of text query image and image query text tasks.

Task	Model	10	30	50	80	100
Text query Image	MLP [80]	0.0181	0.0253	0.0282	0.0310	0.0324
	CNN [81]	0.0179	0.0242	0.0276	0.0303	0.0316
	Transformer [82]	0.0162	0.0231	0.0263	0.0290	0.0304
	RNN [83]	0.0172	0.0246	0.0277	0.0304	0.0319
	LSTM [84]	0.0154	0.0214	0.0248	0.0278	0.0289
	Proposed	**0.0216**	**0.0286**	**0.0315**	**0.0344**	**0.0356**
Image query Text	MLP [80]	0.0256	0.0311	0.0341	0.0378	0.0385
	CNN [81]	0.0193	0.0242	0.0270	0.0299	0.0312
	Transformer [82]	0.0244	0.0312	0.0334	0.0369	0.0383
	RNN [83]	0.0153	0.0241	0.0283	0.0318	0.0332
	LSTM [84]	0.0170	0.0228	0.0256	0.0289	0.0302
	Proposed	**0.0270**	**0.0344**	**0.0375**	**0.0409**	**0.0420**

system's performance by considering its ability to rank relevant results highly, taking into account precision at various recall levels. The MAP score is derived by averaging the Average Precision (AP) scores for all queries in the dataset. In our experiments, we adjust the value of K such as 10, 30, 50, 80, and 100 and conduct comparative tests by substituting the GRU in our image selection model with other architectures like CNN, MLP, LSTM, RNN, and Transformer. The results of these information retrieval experiments are summarized in Table 6. Overall, our model demonstrates superior retrieval performance compared to other benchmark models in both text-to-image and image-to-text retrieval tasks.

5. Discussion

The findings presented in this study demonstrate the critical role of multimodal integration in scientific paper abstract generation. Our structural information enhancement module and combination module successfully bridge the modality gap between textual and visual representations and simultaneously incorporate structural information, addressing a persistent challenge in cross-modal understanding. Compared to conventional text-centric approaches [85], our multimodal framework achieves higher performance. This performance gain validates our hypothesis that complementary information from figures and diagrams can effectively compensate for textual information loss during summarization. Notably, the proposed multi-task learning paradigm introduces an important innovation by simultaneously optimizing for summary quality and image selection. This dual-objective strategy [86] creates a self-reinforcing mechanism where improved image-text alignment facilitates better summary generation, enhancing image selection accuracy. Our ablation studies confirm that removing either the structural information enhancement module or the combination module reduces ROUGE scores, emphasizing their synergistic importance.

The success of our proposed multimodal fusion framework in scientific paper abstract generation provides a methodological foundation for smart city multi-modal data processing. The joint modeling of text coordinates and image layouts through the structural information enhancement module can be transferred to intelligent transportation report parsing scenarios, enabling precise alignment between road network diagrams and accident description texts [87]. Notably, the semantic alignment capability developed through our multi-task learning mechanism can be extended to environmental monitoring data visualization summarization tasks, such as generating joint summaries of air quality sensor data charts and monitoring reports to support rapid decision-making by urban administrators [88].

However, two limitations warrant discussion. First, the current model requires figures to be explicitly labeled using a special method, which may restrict application scenarios. Second, while our dataset covers major computer science fields, domain adaptation challenges may emerge when processing humanities papers or smart city material with different visual conventions. Future work should explore self-supervised pretraining strategies [89] to reduce annotation dependency and investigate dynamic modality weighting mechanisms [90] for heterogeneous document types.

6. Conclusion

In this paper, we present an innovative model for generating abstracts of scientific papers using multimodal fusion and multi-task learning techniques. Additionally, we explore new pathways for multimodal information fusion in smart cities. Our model effectively combines both text and image modalities to enhance the quality of the generated summaries. A significant contribution of our work is the integration of structural information from both text and image modalities through a Structural Information Enhancement Module. We have also developed a Combination Module that enables deep interaction and integration of the enhanced text and image features, capturing the correlation between the two modalities. The Output Module is responsible for generating a multimodal summary while simultaneously selecting the most relevant image to better align the semantics of the image with the text. Unlike previous studies that primarily focus on a single modality, especially textual data, our approach addresses the gap in multimodal content processing. Much of the existing research has centered on text-only materials; our work broadens this focus by incorporating image data, thus enriching the summary generation process. Experimental results demonstrate that our model produces more informative and accurate summaries, showcasing its effectiveness. While the current research is centered on academic literature, the underlying architectural design already incorporates characteristics of urban multimodal data, such as the fusion of traffic flow time-series data and spatial distribution maps. Future work will aim to integrate city-specific data types, including real-time IoT device data streams and multimedia attachments in citizen emergency service tickets, thereby advancing urban governance towards intelligent, multimodal collaborative decision-making paradigms.

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Conflicts of Interest: The authors declare no conflicts of interest.

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