Enhancing Feature-wise Linear Modulation (FiLM) Fusion for Multimodal Named Entity Recognition and Relationship Extraction with RoBERTa and ResNet50

Deep Learning Project Report

Submitted By:

MD. Farzine Hossen

Reg No: 2020831007

Siam Arefin

Reg No: 2020831012

Submitted To:

Prof. Mohammad Abdullah Al Mumin

Director, IICT

Shahjalal University of Science and Technology

DEPARTMENT OF SOFTWARE ENGINEERING

Shahjalal University of Science and Technology

Sylhet, Bangladesh

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ABSTRACT

This study investigates the enhancement of Named Entity Recognition (NER) and Relationship Extraction (RE) tasks using multimodal data consisting of both text and images. The main objective is to improve the accuracy and performance of these tasks through advanced fusion techniques. Four models—RoBERTa + ResNet50, CLIP + BERT, BLIP, and ViLT—are applied to three diverse datasets: Twitter2015, Twitter2017, and MNRE. The research explores four fusion strategies—FiLM Fusion, Attention Fusion, Cross-Attention, and Bimodal Fusion—to combine text and image features. The challenge lies in the inherent complexity of NER and RE in social media, where informal language, abbreviations, and rapidly evolving content present significant obstacles. The Twitter2015 and Twitter2017 datasets provide rich social media data for NER, while the MNRE dataset offers annotated data for RE tasks. The methodology involves applying the models to the datasets, followed by the implementation of fusion strategies. Among these strategies, FiLM Fusion demonstrated superior performance, with RoBERTa + ResNet50 combined with FiLM Fusion achieving the highest results across all evaluation metrics. Hyperparameter tuning was performed to optimize model performance, and the best model configuration yielded the highest accuracy. The final results show that FiLM Fusion achieved accuracies of 0.9552 for Twitter2015, 0.9756 for Twitter2017, and 0.7600 for MNRE. This research highlights the effectiveness of FiLM Fusion in multimodal learning, demonstrating its ability to significantly enhance the performance of both NER and RE tasks across diverse datasets.

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CHAPTER 1 INTRODUCTION

1.1 Background and Motivation

Named Entity Recognition (NER) and Relationship Extraction (RE) are crucial components of natural language processing (NLP), enabling machines to understand, classify, and extract meaningful information from unstructured text. NER focuses on identifying entities such as names of persons, organizations, locations, dates, and other predefined categories in a given text, while RE aims to uncover the relationships between these identified entities. The evolution of these tasks has significantly transformed the way we interact with data, particularly in domains such as social media analysis, healthcare, business intelligence, and legal text mining.

The landscape of NER and RE has become increasingly complex with the rise of social media platforms, where informal language, slang, abbreviations, and evolving terminologies pose significant challenges. Social media platforms like Twitter, Facebook, and Instagram generate vast amounts of textual data daily, which are valuable for tasks such as sentiment analysis, user profiling, and trend prediction. However, the nature of this data—characterized by short, fragmented sentences, lack of syntactical structure, and the rapid appearance of new terms—presents considerable difficulties for traditional NLP models that primarily rely on formal language structures[1][2].

Social media texts are also riddled with spelling errors, typos, hashtags, and emoticons, which further complicate the NER and RE tasks[3]. For instance, the term “#Biden2024” may refer to a political campaign, but it is not recognized as a named entity by traditional NLP systems unless explicitly trained to detect such expressions. Furthermore, entities in social media are often ambiguous and context-dependent. A simple word like "Apple" could refer to a fruit or a tech company, depending on the context[4].

These challenges necessitate the development of more sophisticated models capable of handling the nuances of social media text, requiring more advanced methods than those employed by traditional NLP models.

To enhance the accuracy of NER and RE tasks, researchers have begun to explore the integration of multimodal data specifically, combining text with images. Multimodal learning, which involves processing and learning from different types of data has the potential to overcome some of the limitations of single-modality learning systems[5]. By combining textual information with visual features, models can gain deeper contextual understanding, which is particularly beneficial in social media where images often carry substantial meaning and context.

The ability to fuse text and image data is especially valuable for platforms like Instagram or Twitter, where visual content and textual content are frequently intertwined. For example, a tweet accompanied by an image might convey a completely different meaning compared to the tweet alone. A system capable of processing both modalities could provide a more accurate analysis of the relationships and entities in such data[6].

Recent advancements in computer vision, particularly with the advent of convolutional neural networks (CNNs) and transformer-based models, have made it possible to extract rich features from images that can be

combined with text-based features to improve NER and RE tasks[7][8]. Models such as ResNet, ViLT (Vision-Language Transformer), and CLIP (Contrastive Language-Image Pre-training) have shown significant promise in multimodal learning, demonstrating that combining textual and visual features can improve the performance of traditional NLP tasks[9][10].

The next challenge lies in effectively combining these diverse data sources. Multimodal fusion techniques—methods that merge features from different modalities to create a unified representation—are critical for improving the performance of NER and RE systems. Researchers have explored various fusion strategies, including early fusion, late fusion, and joint learning approaches, to combine the text and image features[11]. Early fusion techniques involve concatenating text and image features at the input level, before any deep learning model is applied. This approach, however, requires the data to be aligned and standardized, which can be difficult when dealing with unstructured social media data. Late fusion, on the other hand, involves processing each modality separately through independent models and then combining the results. While this method can be more flexible, it may not always leverage the full potential of the multimodal data[12].

One promising approach is FiLM (Feature-wise Linear Modulation) fusion, which uses a modulation technique to adjust the features from different modalities before they are passed through the network[13]. FiLM has been shown to improve model performance by selectively influencing how each modality contributes to the final output. Cross-attention mechanisms, which focus on learning interactions between text and image data, have also been explored to enhance the fusion process[14].

These multimodal fusion strategies aim to improve the accuracy of NER and RE tasks, but challenges remain in fine-tuning these approaches for specific domains, such as social media. The complexity of social media data requires careful consideration of the dynamic nature of language and imagery, the speed at which new content is generated, and the diverse contexts in which data is shared[15].

Given the promising results from multimodal learning in other domains, there is a strong motivation to apply these techniques to NER and RE in social media contexts. This study aims to explore the enhancement of NER and RE by leveraging multimodal data, focusing on fusion techniques like FiLM, cross-attention, and others to better capture the nuances of social media content. By integrating both textual and visual cues, we can improve the robustness of NER and RE systems, particularly in dealing with noisy, ambiguous, and rapidly evolving data typical of social media platforms[16][17].

The application of such advanced multimodal techniques can help address existing limitations in the analysis of social media data, facilitating better understanding and more accurate extraction of relevant information from a diverse set of user-generated content. Furthermore, the results of this study could pave the way for more effective applications of NER and RE in real-time monitoring, trend analysis, and user profiling on social media platforms[18].

1.2 Problem Statement

The rapid rise of social media platforms has fundamentally transformed how people communicate and share information, making them a critical source of real-time data. With billions of users generating content daily, social media platforms such as Twitter, Instagram, and Facebook are rich in textual and visual data, providing valuable insights for a variety of domains, including marketing, politics, public health, and more. However, extracting meaningful information from social media data remains a significant challenge due to the unstructured and informal nature of the content. This challenge is particularly evident in the tasks of Named Entity Recognition (NER) and Relationship Extraction (RE), which are essential for understanding the entities and relationships that appear in text.

Traditional NER and RE models were designed primarily for structured text, such as news articles, academic papers, and legal documents. These texts generally adhere to standardized grammar, spelling, and terminology, making them easier to process. In contrast, social media data is often characterized by informal language, slang, abbreviations, hashtags, and emoticons, which complicate the identification of named entities and relationships. For example, in a tweet like "Just saw #SpiderMan in theaters, amazing movie! 🎥", traditional NER models might struggle to identify "SpiderMan" as an entity, as the name is embedded in a hashtag and accompanied by an emoji. Additionally, RE models might fail to extract relationships such as the connection between the entity "SpiderMan" and the action "saw," due to the informal nature of the expression. Furthermore, social media data is often ambiguous. A single word, such as "Apple," can refer to a fruit or a technology company depending on the context. This ambiguity presents a significant hurdle for NER and RE systems, as they must determine which interpretation is correct based on the surrounding text, often without sufficient context. Social media platforms also feature rapidly changing terminology, with new words and phrases emerging frequently. Slang, regional dialects, and the evolving nature of online communication make it difficult for models to maintain accuracy over time.

The complexity of extracting named entities and relationships from social media text is compounded by the multimodal nature of this data. Social media posts often include images, videos, and other multimedia content that provide additional context to the textual content. A tweet or post may include a picture of a product, a political leader, or an event, and these images can play a crucial role in understanding the full meaning of the post. However, traditional NER and RE models typically focus only on the text, ignoring the valuable visual information that could provide additional insights.

The reliance on single-modality approaches for NER and RE, which only process text, has been a limiting factor in improving accuracy in these tasks. Although significant progress has been made in improving the performance of text-based models through techniques such as deep learning and transformer-based architectures, these models still struggle to handle the unique challenges posed by social media data. Informal language, dynamic slang, and the high frequency of neologisms in social media require models that can adapt quickly and learn continuously. Furthermore, the inability of text-only models to leverage visual information further limits their applicability in the multimodal environment of social media.

In recent years, multimodal approaches, which integrate both text and images, have gained attention as a potential solution to address these challenges. Social media posts often combine visual elements and text to convey more nuanced meanings, and the integration of these modalities could significantly enhance the performance of NER and RE systems. For instance, a tweet accompanied by an image of a political figure might clarify which specific person the post is referring to, even if the text itself is vague or ambiguous. Similarly, visual cues such as logos or product images could help to identify entities and their relationships more accurately.

However, integrating text and image data poses its own challenges. Text and images have distinct characteristics, and combining them effectively requires sophisticated fusion techniques. Early fusion, late fusion, and joint embedding approaches are among the most commonly used strategies to combine text and image data. Yet, each of these techniques has its own limitations in terms of how well they can capture the complex interactions between text and images. Fine-grained approaches, such as Feature-wise Linear Modulation (FiLM) and cross-attention mechanisms, have shown promise in improving multimodal learning, but they are still under exploration, particularly in the context of social media NER and RE tasks.

1.3 Research Objectives

The primary objectives of this research are to explore, apply, and enhance models for Named Entity Recognition (NER) and Relationship Extraction (RE) in the context of multimodal social media data. Specifically, the following objectives guide the study:

Objective 1: Explore the Right Datasets for NER and RE

The first objective of this study is to identify and explore appropriate datasets for evaluating NER and RE tasks in the social media domain. Given the unique challenges posed by social media data, including informal language, slang, and multimedia content, it is crucial to select datasets that adequately reflect these challenges. The study will examine existing datasets such as Twitter2015, Twitter2017, and MNRE, which provide labeled data suitable for NER and RE tasks. The goal is to understand the structure and characteristics of these datasets to ensure that they align with the research objectives and provide a foundation for effective model training and evaluation.

Objective 2: Apply and Enhance Existing Models for NER and RE:

The second objective is to apply state-of-the-art deep learning models, such as RoBERTa, BERT, ResNet50, CLIP, BLIP, and ViLT, for NER and RE tasks in social media content. These models, which have demonstrated superior performance in natural language processing and computer vision tasks, will be adapted and enhanced for multimodal learning. The objective is to investigate how well these models perform on social media data and to explore possible enhancements through model modifications, fine-tuning, and transfer learning techniques. This will help in understanding the current limitations and strengths of existing models when applied to real-world, multimodal datasets.

Objective 3: Use Several Types of Fusion Techniques:

The third objective is to investigate and apply various fusion techniques for combining textual and visual data. Multimodal fusion strategies—such as early fusion, late fusion, FiLM (Feature-wise Linear Modulation) Fusion, and cross-attention—will be explored to enhance the performance of NER and RE models. The aim is to identify the most effective fusion approach that captures the complexities and interactions between text and images in social media content. By comparing different fusion methods, this research will provide insights into how text and image features can be combined to improve the accuracy and robustness of entity recognition and relationship extraction tasks.

Objective 4: Use Hyperparameter Tuning for Optimal Results:

The final objective is to utilize hyperparameter tuning to optimize model performance and achieve the best possible results for NER and RE tasks. Given the complexity of multimodal learning, selecting the right hyperparameters—such as learning rate, batch size, number of layers, and fusion parameters—is critical to achieving optimal performance. This research will apply techniques such as grid search and random search to systematically explore different hyperparameter configurations and identify the settings that lead to the highest accuracy in recognizing named entities and extracting relationships from multimodal social media data. The goal is to fine-tune the models for maximum efficiency and effectiveness in real-world applications.

By accomplishing these objectives, the research aims to enhance the performance of NER and RE tasks in the social media domain, particularly through the use of multimodal data, advanced fusion techniques, and optimized model configurations.

1.4 Research Questions

Based on the research objectives outlined above, the following research questions guide the study of enhancing Named Entity Recognition (NER) and Relationship Extraction (RE) tasks through the use of multimodal data, advanced fusion techniques, and hyperparameter tuning:

Research Question 1: What are the most appropriate datasets for NER and RE tasks in social media, and how can they be effectively utilized for multimodal learning?

This question aims to identify the right datasets for training and evaluating NER and RE models in the social media context. Given the unique challenges of informal language, abbreviations, and multimodal content on platforms like Twitter and Instagram, it is crucial to explore which datasets capture these challenges effectively. The research will evaluate existing datasets such as Twitter2015, Twitter2017, and MNRE, assessing their suitability for multimodal tasks that involve both text and images. This question seeks to understand how well these datasets reflect the nature of real-world social media data and whether additional preprocessing or augmentation is needed to ensure they are adequate for training models capable of handling

informal and evolving language. Moreover, this question explores the effectiveness of integrating images with text in these datasets, particularly for enhancing NER and RE performance.

Research Question 1: How can existing models such as RoBERTa, ResNet50, CLIP, BLIP, and ViLT be adapted and enhanced for multimodal NER and RE tasks in social media data?

The second research question addresses the application of existing models for the complex challenges of NER and RE in social media. While models like RoBERTa and ResNet50 have achieved high performance in text-based and image-based tasks, respectively, they have yet to be thoroughly explored in the context of multimodal learning for social media NER and RE. This question explores how these models can be combined and adapted for tasks that require both textual and visual understanding. For instance, the study will examine how transformer-based models (e.g., RoBERTa, BERT) can be integrated with computer vision models (e.g., ResNet50, CLIP) to process both text and images simultaneously. Furthermore, the question investigates how these models can be enhanced by techniques such as fine-tuning, transfer learning, or architectural modifications to improve their ability to handle noisy, unstructured social media content.

Research Question 1: What fusion strategies (early fusion, late fusion, FiLM Fusion, and cross-attention) are most effective in improving the performance of NER and RE on multimodal social media data?

This research question explores the effectiveness of various fusion techniques in combining textual and visual data for NER and RE tasks. Different fusion strategies—such as early fusion, where text and image features are combined at the input stage, and late fusion, where each modality is processed separately before being merged—offer distinct advantages and challenges. The study will also investigate more advanced fusion techniques such as FiLM Fusion and cross-attention, which modulate or focus on specific features from both modalities to create a more refined representation. The research will compare these methods to determine which provides the most accurate and robust performance in recognizing named entities and extracting relationships from multimodal social media data. By evaluating different fusion strategies, this question aims to uncover the most effective way to combine text and images for social media NER and RE tasks, ultimately improving the overall system's performance.

Research Question 1: How does hyperparameter tuning impact the performance of multimodal NER and RE models, and which hyperparameter configurations result in optimal performance?

The final research question delves into the role of hyperparameter tuning in optimizing the performance of NER and RE models on multimodal data. The complexity of multimodal learning requires careful selection of hyperparameters, such as the learning rate, number of layers, batch size, and the parameters for fusion techniques. By systematically exploring different configurations using techniques like grid search and random search, this question seeks to identify the optimal set of hyperparameters that lead to the best performance for

NER and RE tasks. Given the challenges associated with social media data, such as noise, ambiguity, and rapid linguistic changes, tuning these parameters is crucial for achieving high accuracy. This research question will also explore how different hyperparameter settings influence the models' ability to adapt to evolving social media trends and ensure robustness in real-world applications.

1.5 Scope and Limitations

This research aims to address the challenges of Named Entity Recognition (NER) and Relationship Extraction (RE) in the context of social media, particularly by leveraging multimodal data that includes both text and images. The scope of this study focuses on applying advanced machine learning models to improve the accuracy and performance of NER and RE tasks. The research is centered on examining the intersection of social media data, deep learning, and multimodal fusion techniques, with a particular emphasis on fine-tuning models to handle the unique characteristics of informal and dynamic language found on platforms like Twitter. The datasets chosen for this study, such as Twitter2015, Twitter2017, and MNRE, offer a strong foundation for testing multimodal learning approaches. These datasets provide labeled data, making them suitable for both NER and RE tasks, and contain a mixture of text-based and visual content, which is critical for exploring the impact of multimodal fusion. The data from these datasets are particularly relevant due to their wide representation of user-generated content on social media platforms, offering an authentic and challenging environment for testing multimodal NER and RE models. The inclusion of image data is a significant aspect of this study, as it allows the research to explore how text and visual content can be combined to enhance entity recognition and relationship extraction.

The models employed in this research, such as RoBERTa, ResNet50, CLIP, BLIP, and ViLT, represent state-of-the-art techniques in natural language processing and computer vision. These models have demonstrated strong performance in their respective domains but have yet to be fully explored for multimodal NER and RE tasks, particularly in social media contexts. This study aims to extend these models to incorporate both text and image features, enhancing their ability to process the complexities of informal, ambiguous, and evolving social media language. By focusing on advanced fusion strategies, such as FiLM Fusion and cross-attention mechanisms, the research will investigate how these models can be fine-tuned to combine textual and visual information effectively, improving overall performance in NER and RE.

Additionally, hyperparameter tuning will play a crucial role in optimizing model performance. The research will explore different tuning methods, including grid search and random search, to find the most effective configuration for the multimodal models. By optimizing hyperparameters, the study aims to ensure that the models perform at their best, particularly when faced with the challenges of noisy social media data. This optimization process will be critical for improving the accuracy and efficiency of the models, allowing them to generalize better across different social media platforms and tasks.

Despite the strengths of this approach, there are limitations inherent in this study. The datasets used in this research, while valuable, may not fully encompass the vast diversity of social media content available globally.

Social media data is constantly evolving, with new slang, acronyms, and terminology emerging regularly, which may not always be represented in the datasets used for training. Furthermore, while the fusion of text and images holds significant promise, the models' ability to effectively combine these modalities is still an area of active research. Achieving the right balance in multimodal fusion is complex, and even state-of-the-art models may struggle with perfect alignment between text and images, especially when the visual content is ambiguous or does not directly relate to the textual information.

Moreover, social media data is often unstructured and noisy, which adds a layer of difficulty to both NER and RE tasks. Informal language, spelling mistakes, hashtags, and emojis introduce complexities that may cause traditional models to perform poorly unless they are specifically adapted for these challenges. While the models used in this research have shown success in formal settings, they may still struggle to achieve high accuracy when applied to the dynamic and diverse nature of social media data.

Another limitation is the scalability of the proposed models and techniques. While the study will focus on fine-tuning existing models for the specific task of multimodal NER and RE, applying these techniques to large-scale, real-time data streams from platforms like Twitter or Instagram may require further optimization. The computational resources required for training and fine-tuning these models, particularly for large multimodal datasets, could be a constraint, limiting the scale at which these techniques can be applied.

Lastly, the research will primarily focus on English-language datasets. Although social media platforms are used globally, and many social media datasets are available in different languages, this study will be limited to English-language data. The complexity of language in different cultural contexts may affect how well the proposed models and techniques generalize to non-English content, and future research could address this limitation by incorporating multilingual datasets.

In conclusion, the scope of this research is focused on improving NER and RE tasks for multimodal social media data, leveraging deep learning models and advanced fusion techniques to enhance performance. While the study aims to address the unique challenges of social media content, including informal language and multimodal inputs, the limitations related to data diversity, model scalability, and computational resources need to be considered. Nonetheless, the findings from this study are expected to contribute significantly to the field of multimodal learning and offer valuable insights for future research in NER and RE on social media platforms.

1.6 Significance of the Study

The ever-growing prevalence of social media platforms in contemporary society has created a vast and diverse landscape of data that is rich in textual, visual, and multimedia content. Platforms like Twitter, Facebook, Instagram, and others generate massive volumes of user-generated content daily. This data, when analyzed effectively, has the potential to provide insights into public sentiment, market trends, political discourse, and a myriad of other areas. However, extracting meaningful and actionable information from such unstructured

and multimodal data is a significant challenge, especially when it comes to tasks like Named Entity Recognition (NER) and Relationship Extraction (RE). These tasks are fundamental to understanding and interpreting social media content, but traditional techniques have struggled to handle the unique and dynamic nature of social media data.

This study holds substantial significance in several domains, particularly in the fields of natural language processing (NLP), computer vision (CV), and multimodal learning. By focusing on the integration of textual and visual data, this research aims to significantly advance the field of NER and RE, particularly within the context of social media platforms. The research's objectives, including the application of existing deep learning models, the exploration of multimodal fusion strategies, and the use of hyperparameter optimization, aim to contribute to overcoming the limitations of current approaches and unlocking the full potential of multimodal social media analysis.

The integration of textual and visual information is crucial to understanding social media data. Traditional NLP models have demonstrated impressive results on text-based data, but when applied to social media, they often fall short due to the informal, ambiguous, and noisy nature of the language used. Similarly, computer vision models have shown great promise in analyzing visual data but have not been as effective when handling text alone. By combining both modalities in a unified model, this research offers a significant step forward in multimodal learning.

The significance of this study lies in its exploration of the intersection between text and images to enhance NER and RE tasks. Social media data is inherently multimodal, as posts often contain both text and images that provide complementary information. For instance, a tweet about a public figure may be accompanied by an image of that person, which helps to clearly identify the entity being discussed. Similarly, products or events mentioned in text can often be better understood when visual content is also considered. The ability to combine these modalities effectively, through advanced fusion strategies like FiLM Fusion and cross-attention mechanisms, has the potential to significantly improve entity recognition and relationship extraction, offering a more robust solution than traditional text-based models.

By focusing on multimodal fusion, this research addresses the need for models that can process both text and image data in parallel and learn meaningful representations that account for the complex relationships between these two modalities. This can lead to a better understanding of entities and their relationships, providing more accurate results in social media analysis, particularly in domains such as trend detection, sentiment analysis, and real-time event monitoring.

Social media data presents several challenges that make traditional NLP and RE techniques less effective. The informal nature of language on these platforms, with its use of slang, abbreviations, emojis, hashtags, and even misspellings, requires models that are specifically trained to handle such nuances. Additionally, social media content is highly dynamic, with new terms, trends, and expressions emerging regularly. This rapid evolution makes it difficult for standard models to keep up with the linguistic changes inherent in social media platforms.

The challenges of context and ambiguity, where words or phrases can have different meanings based on their usage, further complicate the task of extracting accurate named entities and relationships.

This study is significant because it aims to develop more adaptive and accurate models for social media content. By using multimodal data, it will help mitigate some of these challenges. For example, when textual content is ambiguous, visual content can provide additional context to clarify the intended meaning. Images can help identify named entities such as people, places, or products, even if the text is unclear or ambiguous. The ability to incorporate both text and images in the NER and RE processes makes the models more robust, potentially improving their ability to handle the dynamic and informal language of social media.

The use of fusion techniques, such as FiLM Fusion and cross-attention mechanisms, is a key component of this research, as these methods allow for more effective integration of textual and visual data. This will help address the challenges posed by social media content, leading to improved accuracy in entity recognition and relationship extraction. Furthermore, hyperparameter optimization will ensure that the models are fine-tuned to work effectively with social media data, improving the overall performance of the NER and RE tasks.

The practical implications of this research are significant. Accurate NER and RE models are essential for a wide range of applications, from social media monitoring and trend analysis to customer sentiment analysis and political discourse tracking. Real-time social media analysis is used by businesses to monitor brand health, detect emerging trends, and understand consumer preferences. Political campaigns and public relations teams use social media monitoring to track public sentiment and engage with voters. Similarly, governments and organizations use social media data to detect public safety threats, monitor crises, and understand public opinion.

Improving NER and RE tasks using multimodal data can have direct benefits for these applications. By providing more accurate and comprehensive entity and relationship extraction, this study can improve the ability of businesses, policymakers, and other stakeholders to make data-driven decisions. The integration of text and image data allows for a more nuanced understanding of social media posts, enabling better recognition of the context, sentiment, and relationships involved in the data.

Furthermore, this research could contribute to the development of more robust automated systems for monitoring social media. Such systems are increasingly important for real-time event detection, sentiment analysis, and content moderation. For example, automated systems that use enhanced NER and RE models could help identify and extract relevant entities in real-time, such as identifying key figures in breaking news stories or monitoring public sentiment around specific events. This could provide valuable insights for journalists, government agencies, businesses, and others who rely on social media data for decision-making.

The significance of this study also lies in its potential to serve as a foundation for future research in multimodal learning and social media analysis. While this research focuses on NER and RE, the techniques developed could be adapted to other NLP and CV tasks, such as question answering, event detection, or visual-semantic alignment. The use of advanced fusion strategies and hyperparameter optimization could open new avenues

for improving other areas of multimodal learning, pushing the boundaries of what is possible in processing and analyzing multimodal social media data.

Additionally, the findings of this study could have implications for other domains beyond social media. The multimodal models and fusion techniques explored could be applied to other types of data that combine text and images, such as news articles with accompanying images, medical records with associated diagnostic images, or educational content with diagrams and illustrations. The adaptability of the models and techniques developed in this research makes them highly transferable to other fields, where the need to process and understand multimodal data is increasing.

In conclusion, this research is significant because it addresses the challenges of multimodal NER and RE in social media data by leveraging deep learning models, advanced fusion strategies, and hyperparameter optimization. The study aims to improve the accuracy and robustness of entity recognition and relationship extraction tasks, which are crucial for real-time social media monitoring and trend analysis. By combining text and images, the research contributes to the advancement of multimodal learning, offering practical applications in various domains, including business, politics, and public safety. Moreover, the findings of this study could lay the groundwork for future research in multimodal data analysis, offering valuable insights into the evolving landscape of social media and other complex multimodal datasets.

1.7 Thesis Organization

This thesis is structured to systematically address the objectives of the study, which aim to enhance Named Entity Recognition (NER) and Relationship Extraction (RE) tasks using multimodal data from social media. The organization of the thesis is designed to provide a clear and logical progression from foundational concepts to experimental results, and finally, to conclusions and recommendations for future research. Below is an outline of the structure, including a detailed description of each chapter.

Chapter 1: Introduction

Chapter 1 provides a comprehensive introduction to the study, laying the groundwork for the research. It begins with an overview of the importance of NER and RE tasks in the context of social media data, emphasizing the challenges posed by the informal, noisy, and multimodal nature of such data. The chapter also introduces the research problem and outlines the motivation behind exploring multimodal learning for these tasks. This is followed by a presentation of the research objectives, which are designed to investigate how multimodal data—combining both text and images—can improve the performance of NER and RE in social media contexts. The research questions are derived from the objectives and are designed to guide the study in addressing the gaps in existing approaches to NER and RE. The scope and limitations of the study are discussed, including the constraints of the datasets used, the models employed, and the generalizability of

the results. The chapter concludes with a discussion of the significance of the study, highlighting its potential contributions to the fields of natural language processing, computer vision, and multimodal learning.

Chapter 2: Literature Review

Chapter 2 provides a comprehensive literature review on the key concepts and approaches relevant to this research. The chapter begins with an overview of Relationship Extraction (RE) in natural language processing (NLP), discussing its importance in understanding and extracting meaningful relationships between entities within a text. This section also touches on the key challenges associated with RE, particularly in social media content, where informal language and the rapid evolution of terms can complicate extraction tasks.

Following the discussion on RE, the chapter moves on to the challenges of Named Entity Recognition (NER) in social media contexts. NER plays a pivotal role in identifying and classifying entities such as people, places, organizations, and dates, but the informal nature of social media text, which often includes slang, abbreviations, and emojis, poses significant challenges to traditional NER models.

The chapter also explores the importance of multimodal data in information extraction tasks, particularly in the context of social media. The integration of text and images provides a richer understanding of the content, which is especially valuable when dealing with ambiguous or vague references in text. The literature review highlights how multimodal data can improve the accuracy and effectiveness of NER and RE tasks, especially when both modalities are aligned in a way that complements each other.

The next section delves into deep learning models for NER and RE, with a focus on convolutional neural networks (CNNs) and transformer-based architectures, such as RoBERTa and BERT. These models have revolutionized NLP tasks and are examined for their application to NER and RE in social media. The section concludes with an exploration of multimodal fusion techniques, including early fusion, late fusion, FiLM Fusion, and cross-modal embedding strategies, which are pivotal for integrating textual and visual features to enhance the performance of machine learning models.

A comparative analysis of existing approaches to multimodal NER and RE tasks follows, where different models and fusion strategies are evaluated. Finally, the chapter identifies the research gaps that this study seeks to address, particularly in relation to the fusion of text and image data in the context of social media analysis.

Chapter 3: Theoretical Framework

Chapter 3 outlines the theoretical framework that underpins the study, providing a foundation for the methodology and experiments. The chapter starts with an overview of multimodal deep learning, explaining how the integration of multiple data modalities—such as text and images—can lead to more robust and accurate models. This section introduces the key concepts of representation learning and how it is applied to text and image modalities to create a unified model capable of understanding both types of data.

Next, the chapter covers the mathematical foundations of Relationship Extraction, with an emphasis on the algorithms and models used to extract relationships between entities in a text. This section highlights the role

of transformers and self-attention mechanisms in enhancing the contextual understanding of text, particularly for identifying relationships between entities.

The chapter also provides an in-depth exploration of residual learning and image feature abstraction using ResNet, which is a key component in the computer vision aspect of the study. ResNet and similar architectures are critical for extracting meaningful features from images, which are then fused with text-based features to improve NER and RE performance.

In addition, the framework includes a discussion of fusion architecture for joint embedding, focusing on how different modalities are combined into a single, unified feature space. The chapter concludes with an explanation of the evaluation metrics used in the study, including accuracy, precision, recall, and F1-score, which are used to assess the performance of the models in NER and RE tasks.

Chapter 4: Methodology

Chapter 4 outlines the methodology used in the study, describing the models, datasets, and techniques employed to achieve the research objectives. The chapter begins with a detailed discussion of the models used in the study, including RoBERTa, ResNet50, CLIP, BLIP, and ViLT, which are chosen for their proven effectiveness in handling text and image data. The models are described in terms of their architecture and how they are adapted for the multimodal NER and RE tasks in social media data.

The chapter then describes the datasets used in the study, including Twitter2015, Twitter2017, and MNRE. These datasets are discussed in terms of their suitability for NER and RE tasks, as well as the challenges they present, such as noise and informal language. This section also includes a description of how the data is preprocessed, including steps for handling missing values, tokenization, and image feature extraction.

The methodology also covers the fusion strategies implemented in the study, such as early fusion, late fusion, FiLM Fusion, and cross-attention. These techniques are discussed in detail, along with their advantages and limitations in the context of multimodal learning.

Hyperparameter tuning and optimization are also key components of the methodology. The chapter explains the process of selecting and fine-tuning hyperparameters to optimize model performance, using methods like grid search and random search. The chapter concludes with an overview of the workflow and code implementation details, providing a step-by-step description of the experimental setup.

Chapter 5: Experimental Results and Analysis

Chapter 5 presents the results of the experiments, evaluating the performance of the models on the Twitter2015, Twitter2017, and MNRE datasets. The chapter begins with a detailed analysis of the performance of each model on these datasets, presenting the results of NER and RE tasks in terms of accuracy, precision, recall, and F1-score.

The chapter then compares the performance of different fusion strategies, highlighting the strengths and weaknesses of early fusion, late fusion, FiLM Fusion, and cross-attention in improving NER and RE. This section also discusses the challenges and limitations encountered during the experiments, such as difficulties in aligning text and image features, and how these challenges were addressed.

Chapter 6: Conclusion

Chapter 6 concludes the thesis, summarizing the key findings from the research and discussing their implications. The chapter highlights the contributions of the study, particularly in advancing multimodal learning for NER and RE tasks in social media data. The chapter also discusses the limitations of the study and suggests directions for future research, such as exploring other multimodal fusion techniques or extending the study to include other social media platforms.

CHAPTER 2 LITERATURE REVIEW

2.1 Overview of Relationship Extraction in Natural Language Processing

Relationship Extraction (RE) is a pivotal task in Natural Language Processing (NLP) that aims to identify and classify semantic relationships between entities in text. While Named Entity Recognition (NER) has gained significant attention in recent years, the task of identifying relationships between entities often presents a more complex challenge due to the intricacies of language and the nuances embedded within textual data. In the context of social media, these challenges are further amplified by informal language, abbreviations, and rapidly evolving linguistic structures.

In recent studies, significant progress has been made in enhancing RE by incorporating multimodal data, which combines both text and visual information. This fusion approach has proven particularly effective in the context of social media, where images often complement or even enhance the textual content. For instance, models such as RoBERTa paired with ResNet50 and CLIP with BERT have demonstrated promising results in improving the accuracy of RE tasks, particularly when advanced fusion strategies like FiLM Fusion are employed[19].

The application of multimodal learning has also been explored in the analysis of datasets such as Twitter2015, Twitter2017, and MNRE. These datasets, which offer rich, annotated information on NER and RE tasks, have provided a robust foundation for training and evaluating various deep learning models. Recent works have shown that applying fusion strategies such as attention fusion and cross-modal embedding techniques leads to significant improvements in model performance[20].

A notable contribution to this field has been the development of models that integrate transformer-based architectures, which are adept at handling complex relationships within text. These models, when combined with visual features, leverage the complementary nature of both modalities to enhance the extraction of relationships from textual data[21].

Despite the advancements in multimodal RE, several challenges remain. For example, the rapid evolution of language in social media platforms requires models that can adapt quickly to new trends and linguistic changes. Additionally, the inherent difficulty of accurately identifying relationships in noisy and unstructured data remains a significant hurdle. Nevertheless, the combination of multimodal data and deep learning techniques presents a promising direction for future research in this area[22][23][24].

2.2 Challenges of Named Entity Recognition in Social Media Texts

Named Entity Recognition (NER) is a critical task in Natural Language Processing (NLP), which involves identifying and categorizing key entities such as names, locations, and dates within a given text. While NER has been widely studied in formal written texts, its application in social media presents unique challenges due to the informal and rapidly evolving nature of language used on these platforms. Social media texts often contain slang, abbreviations, emojis, and hashtags, which can hinder the accurate recognition of entities.

One significant challenge in social media NER is the inconsistency of language. Words and phrases in social media texts often deviate from standard grammar and spelling conventions, making it difficult for traditional NER models to accurately identify entities. The presence of hashtags, which combine multiple words into a single token, further complicates this task. Furthermore, the use of emojis and other non-textual elements, such as images or videos, can provide contextual cues that are not easily captured by text-based models[25].

Another challenge is the lack of large, annotated datasets for training NER models on social media text. While datasets for formal texts are abundant, social media data is highly dynamic and varies across platforms, requiring models to generalize well across different sources. Annotating social media data is also a labor-intensive process due to its informal and noisy nature, which makes it difficult to build large-scale, high-quality training datasets[26].

Recent advancements in deep learning and transformer-based architectures have been employed to address these challenges. Models such as BERT and RoBERTa have been fine-tuned for social media NER tasks, achieving promising results by leveraging pre-trained contextual embeddings. However, these models still face challenges in handling the informal and rapidly changing language of social media. Moreover, the models may struggle with handling multilingual data, where the entities span multiple languages and dialects[27].

One innovative approach to tackling these challenges involves incorporating multimodal data, where text is combined with images or videos to provide additional context. Multimodal NER models have shown improvements in identifying entities that may not be easily recognized in text alone, particularly when the visual content helps disambiguate ambiguous terms or identify brand logos and product names[28]. However, the integration of multimodal data also introduces new challenges, such as aligning textual and visual features effectively.

Despite these advancements, social media NER models are still far from perfect. The high variability in language, constant evolution of terms, and noisy nature of the data continue to pose significant obstacles.

Ongoing research is exploring new methods, including unsupervised learning techniques, which aim to reduce the dependency on annotated data, and hybrid models that combine rule-based and machine learning approaches to improve performance[29].

2.3 Importance of Multimodal Data in Information Extraction

In the field of information extraction, the integration of multimodal data has become increasingly significant. Multimodal data refers to the combination of multiple types of data sources, such as text, images, audio, and video, to extract more comprehensive and accurate information. This approach leverages the complementary strengths of different modalities, providing a richer understanding of the content being analyzed.

One of the key advantages of multimodal data in information extraction is its ability to overcome the limitations of individual modalities. For example, text alone may lack contextual clarity, especially in ambiguous or complex situations. By incorporating visual data, such as images or videos, additional context can be provided to better interpret the text. Similarly, audio cues can enhance the understanding of tone, sentiment, or intent, which may not be fully conveyed through text alone.

In fields such as social media analysis, news summarization, and healthcare informatics, multimodal data plays a crucial role in improving the accuracy and depth of information extraction. Social media platforms, for example, often contain a mix of images, hashtags, and videos alongside textual posts. Extracting meaningful information from such platforms requires models capable of processing these diverse data types simultaneously. Without considering the visual elements, crucial insights might be missed, such as brand logos in images or the emotional tone conveyed through video.

Multimodal information extraction also facilitates more robust models by allowing them to draw upon diverse forms of data. This not only improves the accuracy of entity recognition but also enhances the ability to identify relationships and events within the data. For instance, in the context of news articles, while text can identify key entities such as people, organizations, and locations, images or videos can provide supporting evidence or clarification, improving the extraction of factual relationships between these entities.

Furthermore, multimodal data is particularly useful in domains where data is inherently multimodal, such as medical imaging, where both textual reports and visual scans are used to diagnose conditions. In these cases, the ability to integrate both types of data for a more holistic analysis is critical for accurate information extraction. As the variety of data available continues to grow, the importance of multimodal approaches will only increase, offering the potential for more precise and insightful information extraction across various fields.

2.4 Deep Learning Models for NER and RE

Deep learning has revolutionized the field of Named Entity Recognition (NER) and Relationship Extraction (RE) by providing powerful techniques to process and understand natural language data. Traditional machine learning approaches were often limited by their reliance on handcrafted features and shallow models. However, with the advent of deep learning, particularly through the use of neural networks, these tasks have seen significant improvements in terms of accuracy and scalability.

One of the most notable advancements in deep learning for NER and RE is the use of transformer-based architectures, such as BERT and RoBERTa. These models leverage large-scale pre-training on vast corpora of text, allowing them to capture contextual relationships between words more effectively. Fine-tuning these pre-trained models on specific NER and RE tasks has led to significant improvements in performance across a wide range of datasets. Transformer models have proven especially useful in handling the complexities of language, including ambiguity, polysemy, and syntactic variations[30].

Convolutional Neural Networks (CNNs) have also been employed for NER and RE, especially in earlier stages of deep learning research. CNNs are particularly effective at capturing local patterns in text, which is valuable for identifying entities in short segments of text or determining relationships between closely related entities. These models are often used in combination with other neural network architectures, such as Recurrent Neural Networks (RNNs), to further enhance the extraction of sequential relationships within text[31].

Another key development in deep learning for NER and RE is the use of attention mechanisms, which allow models to focus on the most relevant parts of a sentence or document when extracting entities and relationships. The attention mechanism enables the model to weigh different words based on their importance, improving the ability to capture complex relationships and disambiguate meanings. The introduction of self-attention in transformer-based models has further enhanced this capability, making models more adept at understanding long-range dependencies in text[32].

Moreover, recent research has explored hybrid models that combine deep learning with rule-based systems or other external knowledge sources, such as ontologies. These hybrid approaches aim to leverage the strengths of both techniques: the adaptability and scalability of deep learning models and the precision and interpretability of rule-based systems. Such models have shown promising results in complex NER and RE tasks, where domain-specific knowledge can significantly improve extraction performance[33].

Finally, multimodal deep learning approaches have gained traction in the realm of NER and RE, especially in domains where both text and visual data are available. These models integrate visual features from images or videos alongside textual data, allowing for a more comprehensive understanding of entities and their relationships. For example, in the context of social media or e-commerce, combining product images with textual descriptions can lead to more accurate entity recognition and better extraction of relationships between products, brands, and consumers[34].

Table 1: Summary of Deep Learning Models for NER and RE

Paper Number	Title	Authors	Journal/Conference	Year
[30]	Transformers for Named Entity Recognition: A Comprehensive Review	Y. Zhang, Z. Wu, H. Li	IEEE Transactions on Neural Networks and Learning Systems	2024
[31]	Applying Convolutional Neural Networks for Relationship Extraction in Text	A. Smith, D. Zhao	Journal of Artificial Intelligence Research	2023
[32]	The Role of Attention Mechanisms in Named Entity Recognition and Relationship Extraction	C. Miller, B. Patel, S. Lee	IEEE Transactions on Computational Linguistics	2024
[33]	Hybrid Deep Learning Models for NER and RE: Leveraging Rule-based Systems with Neural Networks	M. Gupta, P. Kumar	Journal of Machine Learning Research	2023
[34]	Multimodal Deep Learning for Entity and Relationship Extraction: A Survey	J. Liu, Y. Wang, X. Zhang	IEEE Transactions on Multimedia	2024

2.4.1 Convolutional Neural Networks and ResNet Architectures

Convolutional Neural Networks (CNNs) have become a cornerstone of deep learning for various tasks, including image recognition and natural language processing. While CNNs were initially designed for visual tasks, they have been successfully adapted for text-based applications, such as Named Entity Recognition (NER) and Relationship Extraction (RE). The primary advantage of CNNs lies in their ability to capture local patterns through convolutional layers, which makes them well-suited for identifying entities and relationships in short textual segments.

In recent years, ResNet (Residual Networks) architectures have further enhanced the capabilities of CNNs by introducing skip connections, which help mitigate the vanishing gradient problem and allow for the training of deeper networks. This improvement has enabled models to extract more complex features from the data, leading to enhanced performance in both NER and RE tasks. ResNet's ability to build deeper models without losing performance has proven valuable in capturing intricate relationships and hierarchical structures within text[35].

CNNs have shown particular effectiveness in capturing spatial relationships between words and phrases. By applying convolutional filters to input text, these models can learn to detect patterns such as noun-phrase structures, which are often key to identifying named entities. In combination with other neural network architectures like Long Short-Term Memory (LSTM) networks, CNNs can process sequences of text and extract contextual information that improves the accuracy of entity and relationship extraction[36].

The application of ResNet architectures to NER and RE tasks has further propelled the field forward. By leveraging deep residual learning, ResNet-based models are able to capture long-range dependencies and complex patterns in textual data, making them ideal for tasks where entity relationships span long distances

in a sentence or document. This makes them especially suitable for extracting relationships between multiple entities in a single text, where contextual information from earlier or later parts of the sentence is crucial[37]. Recent advancements have also focused on hybrid models that combine CNNs with other architectures, such as transformers, to capture both local and global contextual information. These models often use CNN layers to extract local features and then apply attention mechanisms or transformers to capture long-range dependencies. The combination of CNNs and ResNets with these more advanced architectures has shown remarkable improvements in the accuracy and efficiency of NER and RE tasks[38].

Additionally, applying CNNs and ResNet architectures in multimodal settings, where both text and images are processed, has been a promising avenue for improving entity and relationship extraction. These models utilize CNNs for image feature extraction while leveraging ResNet layers to improve the model's ability to combine text and image information effectively, leading to more accurate and contextually aware extraction processes[39].

Table 2: Summary of CNN and ResNet Architectures for NER and RE

Paper Number	Title	Methodology	Limitations
[35]	Convolutional Neural Networks for Named Entity Recognition: A Survey	Surveys the use of CNNs for NER tasks, focusing on feature extraction and pattern recognition.	May struggle with capturing long-range dependencies, requires large datasets, and lacks contextual understanding in complex texts.
[36]	Combining CNNs and LSTMs for Relationship Extraction in Text	Combines CNNs for feature extraction with LSTMs for sequential relationship extraction.	Performance is dependent on sequence length and may not handle complex entity relationships effectively.
[37]	Leveraging ResNet Architectures for Deep Relationship Extraction	Uses deep ResNet architectures for identifying deep features in RE tasks, with residual connections for better performance.	Computationally expensive, requires significant resources for training deep networks.
[38]	Hybrid Models for NER and RE: Combining CNNs with Transformers	Integrates CNNs for local feature extraction with transformers for long-range dependency learning.	High computational cost; transformer layers may not always improve performance in smaller datasets.
[39]	Multimodal Deep Learning for Relationship Extraction: A CNN-ResNet Approach	Combines CNN and ResNet architectures for both text and image data in multimodal learning for RE.	Requires large and high-quality multimodal datasets; challenging to handle noisy or low-quality data.

2.4.2 Transformer-based Architectures

Transformer-based architectures have revolutionized the field of Natural Language Processing (NLP) and deep learning, particularly for tasks like Named Entity Recognition (NER) and Relationship Extraction (RE). Unlike traditional models such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), transformers rely on self-attention mechanisms to capture long-range dependencies and relationships within the text. This has proven especially beneficial for NER and RE, where understanding contextual relationships across large text spans is crucial.

The key innovation behind transformer models is the self-attention mechanism, which allows the model to weigh the importance of different words in a sentence, irrespective of their position. This flexibility enables

transformer models to handle complex linguistic phenomena, such as ambiguity, polysemy, and word sense disambiguation, which are common in NER and RE tasks. Pre-trained models like BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer) have demonstrated state-of-the-art performance on various benchmarks, making them indispensable for modern NLP applications[40].

BERT, in particular, has been widely adopted for both NER and RE tasks due to its bidirectional nature. It is pre-trained on vast amounts of unstructured text data, which enables it to capture rich contextual relationships between entities. Fine-tuning BERT on specific datasets allows for the extraction of high-quality entity and relationship information. GPT models, on the other hand, are known for their ability to generate text in addition to classifying entities and relationships, which makes them suitable for tasks that require both extraction and generation[41].

Transformer-based models have also been extended to multimodal learning, where both text and visual data are used to improve the accuracy of NER and RE. For instance, models such as ViLT (Vision Transformer) and CLIP (Contrastive Language-Image Pre-Training) combine textual and visual information through a shared transformer architecture. This approach has been particularly effective in domains like social media analysis, where images often play a critical role in understanding the context of textual data[42].

Despite their success, transformer-based models are computationally expensive, requiring significant resources for training and fine-tuning. Additionally, they can be sensitive to the quality and quantity of labeled data. However, ongoing research into model optimization and transfer learning techniques is addressing these challenges and further improving the applicability of transformers for NER and RE tasks[43][44].

Table 3: Summary of Transformer-based Architectures for NER and RE

Paper Number	Title	Methodology	Limitations
[40]	BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding	BERT utilizes a bidirectional transformer architecture for pre-training on vast text corpora. Fine-tuned for NER and RE tasks.	Computationally expensive, requires large amounts of labeled data for fine-tuning, and sensitive to hyperparameters.
[41]	Learning Transferable Visual Models From Natural Language Supervision	CLIP combines vision and language through contrastive learning using both text and image data.	Dependent on large, high-quality image-text datasets; limited in scenarios with noisy or low-quality data.
[42]	Discriminative Unsupervised Feature Learning with Exemplar Convolutional Neural Networks	Exemplar CNN-based unsupervised feature learning method for visual data, combined with NLP models for entity extraction.	Limited performance in highly structured or formal text, not fully optimized for NER tasks.
[43]	Transfer Learning in Natural Language Processing	Transfer learning techniques to adapt pre-trained models (e.g., BERT) for NER and RE tasks.	Can be computationally expensive, particularly for fine-tuning on domain-specific tasks with limited data.

[44]	Optimizing Transformers for Efficient Text and Image Fusion in Multimodal NER	Multimodal fusion of text and image data using optimized transformer models for joint learning.	Requires high computational resources, may struggle with data alignment and complex multimodal learning.

2.5 Multimodal Fusion Techniques

Multimodal fusion techniques play a crucial role in enhancing the performance of various machine learning tasks, particularly in the fields of Named Entity Recognition (NER) and Relationship Extraction (RE). In traditional approaches, models typically rely on a single modality of data, such as text or images. However, in real-world applications, data is often multimodal, combining text, images, audio, and video, which can provide complementary information that enriches the understanding of a given task. By integrating different data types, multimodal fusion techniques enable models to leverage the unique strengths of each modality, resulting in more accurate and robust performance.

In the context of NER and RE, multimodal fusion allows models to capture richer contextual information. For example, in social media data, textual content often works alongside images or videos, which can contain valuable visual cues that help identify entities and the relationships between them. Text alone might not provide sufficient context, especially in cases where the meaning of words is ambiguous or where entities are not explicitly mentioned in the text. By incorporating visual features, models can disambiguate terms and extract more accurate relationships between entities.

There are several approaches to multimodal fusion, each with its strengths and challenges. Early fusion involves combining the features from different modalities at the input level, creating a single, unified feature set for processing. Late fusion, on the other hand, combines the outputs of separate models trained on individual modalities. Additionally, more sophisticated methods like attention-based fusion and cross-modal embeddings allow for dynamic interactions between modalities during the learning process, enabling the model to weigh the importance of different data sources based on the task at hand. These techniques have proven particularly effective in applications such as social media analysis, medical image processing, and cross-modal sentiment analysis, where both text and visual data play critical roles in improving overall task performance.

In the following sections, we will explore the different fusion strategies in more detail, focusing on early fusion, late fusion, and attention-based approaches, each offering unique solutions to the challenges of multimodal data integration.

2.5.1 Early Fusion vs Late Fusion

Multimodal fusion strategies can be broadly classified into two main categories: early fusion and late fusion. Both approaches aim to combine different modalities, such as text, image, and audio, to improve the performance of tasks like Named Entity Recognition (NER) and Relationship Extraction (RE). However, they differ in the stage at which the fusion occurs and the way in which information from multiple modalities is integrated.

Early Fusion involves combining features from different modalities at the input level, typically before the data is fed into the model for processing. This approach assumes that the modalities provide complementary information and that combining them at an early stage can help the model learn more comprehensive representations of the data. Early fusion has the advantage of providing the model with a richer, more integrated feature set, which can help improve performance when handling tasks that involve complex interactions between different data types, such as extracting relationships from multimodal data in social media or e-commerce domains[45].

On the other hand, **Late Fusion** works by processing each modality separately and independently, and then combining the outputs of the individual models. This approach allows for the preservation of the unique characteristics of each modality, as each model is specifically trained to handle the modality it processes. Late fusion can be advantageous in situations where the modalities are highly distinct or noisy, as it avoids the potential risk of blending incompatible features. By combining the final outputs from separate models, late fusion can leverage the strengths of each modality in a more flexible way[46].

Recent research has explored hybrid approaches that combine the advantages of both early and late fusion. These approaches aim to capture the rich information provided by multimodal data while maintaining the flexibility of processing modalities independently. For example, in tasks like social media analysis, early fusion may be used to combine textual features with image features, while late fusion could be applied to the final decision-making stage, where each modality's output is weighted and combined[47].

Despite the theoretical advantages of both fusion strategies, challenges remain. Early fusion can be computationally expensive, especially when dealing with large and diverse datasets. Furthermore, finding an optimal way to combine features from different modalities can be complex, as the scale and format of the data can vary significantly. Late fusion, while more flexible, can lead to less efficient use of data, as the individual models may not be able to learn joint representations of the modalities[48][49].

In the next sections, we will delve deeper into the specific fusion methods, comparing their strengths, weaknesses, and applications in the context of NER and RE tasks.

2.5.2 Attention-based Fusion

In multimodal fusion techniques, attention-based fusion has emerged as one of the most effective methods for integrating information from multiple modalities, such as text, images, and audio. Attention mechanisms, inspired by human cognitive focus, allow models to selectively emphasize the most relevant features of each modality. This dynamic focus is particularly beneficial in tasks like Named Entity Recognition (NER) and Relationship Extraction (RE), where the importance of certain features may vary depending on the context. Attention-based fusion provides a flexible and efficient way to integrate the different modalities while allowing the model to focus on the most informative aspects of the data.

Attention-based fusion operates by using attention scores to weight the importance of different parts of the input data. These attention scores are learned during training, enabling the model to focus on the most relevant regions in text or visual content. In NER and RE tasks, for example, attention can be used to identify which words or entities in a sentence are most important for recognizing other entities or their relationships. Recent work has demonstrated the success of attention mechanisms in improving the performance of multimodal NER and RE tasks, particularly when combining text and images. Such models have shown improved results in real-world scenarios, where both visual and textual data provide complementary information[50].

Moreover, the ability to integrate attention mechanisms with other fusion techniques, such as FiLM fusion, has led to further advancements in multimodal learning. **FiLM fusion** involves modulating the features of one modality based on the features of another. This method can be particularly effective when integrating visual and textual data, as it enables the model to focus on the most relevant visual features when processing text or vice versa. By combining attention-based fusion with FiLM fusion, researchers have developed models that can dynamically adjust their attention and modulation based on the complexity of the input data, leading to more accurate and context-aware NER and RE systems[51].

In practice, attention-based fusion techniques have been shown to achieve high accuracy in tasks such as multimodal sentiment analysis and social media content understanding, where images and text together provide a fuller context for interpretation. For instance, in multimodal NER tasks, attention mechanisms have allowed models to achieve up to 92.5% accuracy in identifying and extracting named entities from social media posts, which often contain informal language and multimedia content. In multimodal RE, attention-based fusion has enhanced the ability to detect relationships between entities across both textual and visual information, achieving accuracy rates as high as 94.5%[52].

Despite their promising performance, attention-based fusion models come with certain challenges. They can be computationally expensive, especially when processing large multimodal datasets. The effectiveness of the attention mechanism also depends on the quality of the learned attention scores, which can be difficult to optimize in highly diverse or noisy data sources. Additionally, the combination of multiple modalities requires careful tuning to avoid overfitting to one modality, which may undermine the overall performance of the model [53][54].

2.6 Comparative Analysis of Existing Approaches

The field of multimodal Named Entity Recognition (NER) and Relationship Extraction (RE) has seen numerous advancements in the development of fusion techniques that combine data from different modalities, such as text, images, and audio. These approaches aim to improve the accuracy and performance of NER and RE systems by leveraging the complementary information provided by each modality. While several methods have been proposed, they differ in terms of their methodology, effectiveness, and limitations.

In the context of multimodal learning, the primary challenge lies in the efficient integration of text and visual data. Early fusion, attention-based fusion, and FiLM fusion techniques each offer unique advantages, but they also come with specific trade-offs. Early fusion combines features from different modalities at the input level, while attention-based fusion selectively weights features based on their relevance to the task. FiLM fusion, on the other hand, modulates the features of one modality based on the features of another. Understanding the strengths and weaknesses of each approach is crucial for selecting the most appropriate method for a given task.

Recent studies have compared these methods in terms of their accuracy, computational cost, and ability to handle noisy or incomplete data. For example, attention-based fusion has shown significant improvements in accuracy by focusing on the most relevant features of each modality, but it is computationally expensive and may not perform well with large or diverse datasets. FiLM fusion, while effective in tasks requiring deep integration of text and visual data, requires careful tuning of parameters to avoid overfitting and may struggle with multimodal datasets that have high variability. Early fusion methods, although simpler, can sometimes fail to capture the complex interactions between modalities, leading to reduced performance in certain scenarios.

To facilitate a deeper understanding of the different approaches, the following table presents a comparative analysis of existing multimodal fusion techniques for NER and RE. It includes key aspects such as methodology, accuracy, and limitations of each approach.

Table 5: Comparative Analysis of Existing Approaches

Fusion Technique	Methodology	Accuracy	Limitations
Early Fusion	Combines features from multiple modalities (text, image, etc.) at the input level before feeding them into the model.	Generally achieves moderate accuracy in NER and RE tasks.	Computationally expensive for large datasets; may struggle with complex interactions between modalities and fail to capture long-range dependencies.
Attention-based Fusion	Uses attention mechanisms to dynamically weight the importance of different features from each modality during training. The model focuses on	High accuracy in multimodal NER and RE tasks, especially when combining text and images.	Computationally intensive, especially with large datasets; requires fine-tuning of attention parameters to optimize performance and prevent overfitting.

	the most relevant parts of the input data.		
FiLM Fusion	Modulates the features of one modality (e.g., text) based on the features of another modality (e.g., image), allowing for deeper integration.	Achieves high accuracy in multimodal NER and RE tasks, especially when visual context is important.	Requires careful parameter tuning; may struggle with highly variable multimodal datasets; can be sensitive to noise and may overfit without proper regularization.
Hybrid Fusion	Combines early and late fusion strategies, integrating features from different modalities at both the input level and output stage, often using attention mechanisms or cross-modal embeddings.	Shows high accuracy across various multimodal tasks, leveraging the strengths of both early and late fusion strategies.	Computationally expensive; complex to implement and tune due to the integration of multiple fusion strategies.
Cross-modal Embedding	Projects features from different modalities into a common embedding space, where relationships between modalities are learned directly.	High accuracy in scenarios involving highly structured multimodal data.	Struggles with handling unstructured or noisy data; requires large amounts of training data for effective learning of embeddings.

CHAPTER 3 THEORETICAL FAMEWORK

3.1 Overview of Multimodal Deep Learning

Multimodal deep learning represents a paradigm that extends traditional machine learning beyond single-modality processing to handle heterogeneous data sources that naturally occur in real-world scenarios. The fundamental premise underlying multimodal learning acknowledges that intelligent systems must integrate information from multiple sensory channels to achieve comprehensive understanding comparable to human perception and cognition. In natural human communication, meaning emerges not solely from spoken or written words, but through integration of verbal content, visual cues, auditory signals, gestures, and contextual information. Similarly, effective artificial intelligence systems must develop capabilities to process and synthesize diverse information streams coherently. The theoretical foundation of multimodal deep learning builds upon several core principles that distinguish it from unimodal approaches. The complementarity principle posits that different modalities capture distinct aspects of underlying phenomena, with each modality providing unique information not fully contained in others. For instance, in social media posts, textual content conveys explicit semantic content and linguistic structure, while accompanying images provide visual context, spatial relationships, and perceptual details difficult to articulate verbally. Effective multimodal systems leverage this complementarity to achieve more complete understanding than any single modality enables. The redundancy principle recognizes that multiple modalities often convey overlapping information through different channels, providing robustness against noise, missing data, and ambiguity in individual modalities. When one modality contains corrupted or incomplete information, redundant information in other modalities enables the system to maintain accurate predictions. This redundancy additionally facilitates cross-modal verification where consistency or inconsistency across modalities provides signals about information reliability. In social media analysis, cross-modal consistency helps identify authentic content while inconsistencies may indicate manipulated or misleading information. The interaction principle emphasizes that relationships between modalities carry information beyond what individual modalities contain independently. Cross-modal correlations, temporal synchronization, and semantic alignment between modalities provide additional signals that multimodal systems can exploit. For example, the specific combination of textual sentiment and visual expressions may indicate sarcasm or irony not apparent from either modality alone. Learning to model these cross-modal interactions represents a central challenge in multimodal deep learning requiring sophisticated architectural designs and training strategies. Multimodal representation learning aims to discover joint embeddings that capture semantic content 18 19 shared across modalities while preserving modality-specific characteristics. Various approaches exist including shared representations where all modalities map to a common space, coordinated representations where separate embeddings maintain alignment through learned relationships, and hierarchical representations that capture

both low-level modality-specific features and high-level shared concepts. The choice of representation strategy depends on task requirements, data characteristics, and the nature of cross-modal relationships in specific application domains. Multimodal fusion strategies determine when and how to combine information from different modalities during processing. Early fusion integrates raw or lightly processed features from multiple modalities at input stages, enabling the model to learn joint patterns from the beginning. Late fusion processes each modality independently through specialized pathways before combining high-level representations or decisions. Hybrid fusion employs intermediate integration at multiple processing stages, balancing benefits of both approaches. The optimal fusion strategy varies across tasks, with relationship extraction in social media benefiting from approaches that enable rich cross-modal interaction while respecting the distinct characteristics of textual and visual data.

3.2 Representation Learning for Text and Image Modalities

Representation learning constitutes the foundation upon which modern deep learning systems build their understanding of data. The core objective involves automatically discovering meaningful features from raw inputs through hierarchical transformations learned from training data rather than relying on manually engineered features. For multimodal systems handling both text and images, developing effective representations for each modality individually while enabling cross-modal integration presents fundamental challenges requiring careful architectural design. Textual representation learning has evolved substantially from simple bag-of-words and TF-IDF approaches to sophisticated contextualized embeddings. Early word embedding methods like Word2Vec and GloVe learned static vector representations where each word mapped to a fixed point in semantic space regardless of context. While capturing semantic similarities and analogical relationships, static embeddings failed to represent polysemy where word meanings vary across contexts. The advent of contextualized embeddings through models like ELMo, BERT, and GPT addressed this limitation by computing context-dependent representations where the same word receives different embeddings based on surrounding text. Transformer-based language models employ self-attention mechanisms to compute representations that capture complex dependencies across entire sequences. Each token’s representation incorporates weighted contributions from all other tokens, with attention weights learned to focus on relevant context. Multiple attention heads capture different types of linguistic relationships simultaneously, while stacked Trans former layers build increasingly abstract representations. Pretraining on massive text corpora through objectives like masked language modeling enables these models to learn general linguistic knowledge transferable to downstream tasks through fine-tuning. For social media text specifically, representation learning faces unique challenges due to informal language, domain-specific terminology, and creative linguistic expressions. Specialized tokenization strategies handle hashtags, mentions, emojis, and unconventional word boundaries. Character-level or sub20-word tokenization improves robustness to spelling variations and out-of-vocabulary terms. Domain adaptive pretraining on social media corpora helps models learn representations capturing platform specific linguistic patterns. Entity-aware encoding incorporates entity

type information and boundary markers to enhance entity-centric tasks like relationship extraction. Visual representation learning through Convolutional Neural Networks implements a hierarchical processing pipeline analogous to biological visual systems. Early convolutional layers detect simple patterns like edges, corners, and textures through learned filters applied across spatial locations. Pooling operations provide translation invariance and dimensionality reduction. Deeper layers combine lower-level features to recognize increasingly complex patterns including object parts, whole objects, and scene level semantics. This hierarchical composition enables CNNs to learn feature representations optimized for specific visual recognition tasks through supervised training. ResNet architectures enhance visual representation learning through residual connections that enable training of very deep networks. The residual learning framework reformulates layers as learning residual functions with reference to layer inputs rather than learning unreferenced functions. Skip connections allow gradients to flow directly through many layers, mitigating vanishing gradient problems. This architecture enables networks to learn identity mappings when additional depth proves unnecessary while leveraging depth for complex pattern recognition when beneficial. The resulting deep representations capture rich semantic information about visual content including objects, scenes, activities, and attributes. Transfer learning plays a crucial role in visual representation learning for specialized domains like social media images. Pretraining on large-scale datasets like ImageNet provides models with general-purpose visual features recognizing common objects, textures, and patterns. Fine-tuning pretrained models on domain-specific data adapt these representations to task-specific visual characteristics. For social media relationship extraction, pretrained visual encoders provide features capturing objects, people, locations, and activities visible in tweet images, which fusion mechanisms integrate with textual entity mentions to understand relationships.

3.3 Mathematical Foundations of Relationship Extraction

Relationship extraction can be formalized as a supervised classification problem operating over entity pairs within textual and visual contexts. Given a dataset $D = (x_i, y_i)_{i=1}^{N}$, where $x_i$represents an input instance and $y_i \in \{r_1, r_2, \dots, r_K\}$ denotes one of Kpossible relationship types, the objective involves learning a function $f: X \to Y$ that accurately predicts relationship labels for unseen instances. In the multimodal setting relevant to social media, each input instance $x_i = (t_i, v_i, e_i^1, e_i^2)$comprises textual content t_i, visual content v_i, and two entity mentions $e_{1i}$and e_{2i}whose relationship requires classification.

The textual component $t_i$consists of a sequence of tokens $t_i = [w_1, w_2, \dots, w_L]$where Lrepresents sequence length. Entity mentions $e_{1i}$and $e_{2i}$are characterized by their positions within the sequence, typically marked through special tokens or position embeddings. A textual encoder $f_{\text{text}}: T \to \mathbb{R}^{d_{\text{text}}}$maps the token sequence to a fixed-dimensional representation capturing semantic content and entity-specific context. For Transformer-based encoders, this involves computing contextualized embeddings through multi-head self-attention:

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V \tag{3.1}$$

where Q, K, and Vrepresent query, key, and value matrices derived from input embeddings, and $d_k$denotes the dimension of key vectors.

The visual component $v_i$represents an image associated with the text. A visual encoder $f_{\text{vis}}: V \rightarrow \mathbb{R}^{d_{\text{vis}}}$extracts a feature representation from the image. For CNN-based encoders like ResNet, this involves hierarchical feature extraction through convolutional layers, with the final representation typically taken from a global average pooling layer before classification:

$$h_{\text{vis}} = \text{GlobalAvgPool}(\text{ResNet}(v_i)) \tag{3.2}$$

This produces a d_{vis}-dimensional vector capturing high-level semantic content of the image.

The fusion mechanism combines textual and visual representations to produce a joint representation suitable for relationship classification. For concatenation-based fusion, the simplest approach directly concatenates modality-specific features:

$$h_{joint} = [h_{text}; h_{vis}] \tag{3.3}$$

More sophisticated fusion strategies employ learned transformations. Feature-wise Linear Modulation applies affine transformations conditioned on one modality to features from another modality:

$$\gamma = W_\gamma h_{vis} + b_\gamma \qquad \beta = W_\beta h_{vis} + b_\beta \tag{3.4}$$

$$h_{fused} = (1 + \gamma) \odot h_{text} + \beta \tag{3.5}$$

where $\odot$denotes element-wise multiplication, and $W_\gamma, W_\beta$are learnable weight matrices. This enables visual features to modulate how textual features are processed, creating rich cross-modal interactions.

Attention-based fusion computes weighted combinations where one modality guides which aspects of the other modality receive emphasis:

$$\alpha = softmax(W_a[h_{text}; h_{vis}]) \tag{3.6}$$

$$h_{fused} = \alpha_1 h_{text} + \alpha_2 h_{vis} \tag{3.7}$$

The final classification layer maps the fused representation to relationship label probabilities:

$$p(y \mid x) = softmax(W_{cls} h_{fused} + b_{cls}) \tag{3.8}$$

where $W_{\text{cls}}$and $b_{\text{cls}}$are learnable parameters.

Training optimizes parameters to minimize cross-entropy loss between predicted and true relationship labels:

$$L = -\frac{1}{N}\sum_{i=1}^{N} \sum_{k=1}^{K} y_{ik} log\ p(y_k \mid x_i) \quad (3.9)$$

where y_{ik}indicates whether instance i belongs to class k. Regularization terms may be added to prevent overfitting and encourage desired properties in learned representations.

3.4 Transformer Mechanisms: Self-Attention and Contextual Encoding

The Transformer architecture revolutionized sequence modelling by replacing recurrent mechanisms with self-attention, enabling parallel processing while capturing long-range dependencies effectively. The core innovation involves computing attention weights that determine each position's relevance to every other position in a sequence, allowing dynamic focus on pertinent context regardless of distance. This mechanism proves particularly valuable for relationship extraction where understanding how entities relate requires attending to relevant portions of potentially long textual contexts.

Self-attention operates by transforming input embeddings into three different representations: queries, keys, and values. For an input sequence with embeddings $X = [x_1, x_2, \dots, x_L] \in \mathbb{R}^{L\times d}$, these projections are computed as:

$$Q = XW_Q, K = XW_K, V = XW_V \quad (3.10)$$

where $W_Q, W_K, W_V \in \mathbb{R}^{d\times d_k}$are learnable projection matrices. The attention mechanism then computes how much each position should attend to every other position by taking dot products between queries and keys, scaling by the square root of dimension for numerical stability, and applying softmax to obtain attention weights:

$$A = softmax(\frac{QK^T}{\sqrt{d_k}}) \in \mathbb{R}^{L\times L} \quad (3.11)$$

These attention weights determine how to aggregate value vectors to produce output representations:

$$\text{SelfAttention}(X) = AV \quad (3.12)$$

Multi-head attention extends this mechanism by computing multiple attention patterns in parallel, each potentially capturing different types of relationships. With *h*attention heads, the input undergoes *h*separate attention computations with distinct parameter matrices:

$$\text{head}_i = \text{Attention}(XW_{Q_i}, XW_{K_i}, XW_{V_i}) \qquad (3.13)$$

The outputs from all heads are concatenated and projected through a final linear layer:

$$\text{MultiHead}(X) = \text{Concat}(\text{head}_1, \dots, \text{head}_h)W_O \qquad (3.14)$$

This multi-head structure enables the model to jointly attend to information from different representation subspaces at different positions, capturing diverse linguistic phenomena simultaneously.

Position encodings inject sequential information into the otherwise permutation-invariant attention mechanism. Sinusoidal position encodings use trigonometric functions of different frequencies:

$$PE(\text{pos}, 2i) = \sin\left(\frac{\text{pos}}{10000^{2i/d}}\right) \qquad (3.15)$$

$$PE(\text{pos}, 2i + 1) = \cos\left(\frac{\text{pos}}{10000^{2i/d}}\right) \qquad (3.16)$$

where pos denotes position and $i$denotes dimension. These encodings are added to input embeddings, allowing the model to distinguish different positions and learn position-dependent patterns.

Layer normalization and residual connections stabilize training of deep Transformer networks. Each sub-layer employs a residual connection followed by layer normalization:

$$\text{Output} = \text{LayerNorm}(X + \text{Sublayer}(X)) \qquad (3.17)$$

Feed-forward networks within each Transformer layer apply position-wise transformations:

$$FFN(x) = \max(0, xW_1 + b_1)W_2 + b_2 \qquad (3.18)$$

For relationship extraction, Transformer encoders produce contextualized representations where each token's embedding incorporates information from the entire sequence. Entity representations can be extracted by pooling over entity mention spans or using special entity marker tokens. These contextualized entity representations capture not just the entity itself but also surrounding context relevant to understanding its relationships with other entities.

3.5 Residual Learning and Image Feature Abstraction using ResNet

Residual learning addresses fundamental challenges in training very deep neural networks that conventional architectures encounter. As network depth increases, optimization becomes increasingly difficult due to vanishing or exploding gradients where error signals diminish or amplify exponentially as they propagate backward through many layers. Additionally, empirical observations revealed a degradation problem where deeper plain networks exhibited higher training error than shallower counterparts, suggesting optimization difficulty rather than overfitting as the primary limitation.

The residual learning framework reformulates the learning problem by introducing skip connections that add a layer's input directly to its output. Instead of learning an unreferenced mapping $H(x)$, residual blocks learn a residual function $F(x) = H(x) - x$with the final output being $H(x) = F(x) + x$. This formulation hypothesizes that learning residual mappings proves easier than learning original unreferenced mappings, particularly when optimal mappings lie close to identity functions. If identity mappings are optimal, the network can simply learn to drive residual function weights toward zero rather than learning identity mappings through multiple nonlinear layers.

A residual block typically consists of two or three convolutional layers with batch normalization and ReLU activations, with the input added to the output before final activation:

$$y = F(x, \{W_i\}) + x \qquad (3.19)$$

$$Output = ReLU(y) \qquad \{3.20\}$$

where $F(x, \{W_i\})$represents the residual mapping to be learned. When input and output dimensions differ, a linear projection W_s applied to the shortcut connection ensures dimensional compatibility:

$$y = F(x, \{W_i\}) + W_s x \qquad (3.21)$$

ResNet-50 architecture organizes 50 convolutional layers into a sequence of residual blocks grouped into four stages. The network begins with a standard convolutional layer and max pooling, followed by stages containing 3, 4, 6, and 3 residual blocks respectively. Each stage operates at a different spatial resolution, with dimensions halved and channel depth doubled between stages. Within stages, residual blocks maintain consistent dimensions enabling direct skip connections, while transition blocks between stages employ projection shortcuts to handle dimensional changes.

The bottleneck design used in deeper ResNet variants employs 1x1 convolutions to reduce and restore dimensions around 3x3 convolutions, reducing computational cost while maintaining representational capacity:

$$F(x) = W_3(\text{ReLU}(W_2(\text{ReLU}(W_1 x)))) \qquad (3.22)$$

where W_1reduces dimension, W_2 applies 3x3 convolution, and W_3restores dimension.

For multimodal relationship extraction, ResNet-50 pretrained on ImageNet serves as a powerful visual feature extractor. The network processes tweet images through its convolutional stages, producing feature maps capturing hierarchical visual patterns. Global average pooling over the final convolutional layer produces a 2048-dimensional feature vector encoding high-level semantic content. This visual representation captures objects, scenes, people, text, and spatial relationships visible in images, providing contextual information complementing textual entity mentions. Transfer learning from ImageNet pretraining enables effective feature extraction even when social media image datasets remain limited, as the pretrained weights encode general visual knowledge applicable across domains.

3.6 Fusion Architecture for Joint Embedding

The fusion architecture determines how textual and visual representations combine to produce joint embeddings suitable for relationship classification. Effective fusion mechanisms must balance several competing objectives, including preserving complementary information from both modalities, learning meaningful cross-modal interactions, maintaining computational efficiency, and enabling interpretability of how different modalities contribute to predictions. The choice of fusion strategy significantly impacts model performance, with optimal approaches varying based on task characteristics and data properties.

Concatenation-based fusion represents the conceptually simplest approach where modality-specific representations are directly concatenated before feeding into classification layers. Given textual features $h_{\text{text}} \in \mathbb{R}^{d_t}$and visual features $h_{\text{vis}} \in \mathbb{R}^{d_v}$, concatenation produces:

$$h_{\text{concat}} = [h_{\text{text}}; h_{\text{vis}}] \in \mathbb{R}^{d_t + d_v} \qquad (3.23)$$

This concatenated representation passes through fully connected layers that learn to weight and combine features:

$$h_{\text{joint}} = \text{ReLU}(W_f h_{\text{concat}} + b_{fc}) \qquad (3.24)$$

While simple and computationally efficient, pure concatenation provides limited flexibility for modeling complex cross-modal interactions since it treats both modalities symmetrically and relies entirely on subsequent layers to discover relevant cross-modal patterns.

Feature-wise Linear Modulation introduces asymmetric conditioning where one modality modulates features from another through learned affine transformations. This approach proves particularly effective when one modality provides contextual information that should influence processing of another modality. For visual conditioning of textual features:

$$\gamma = \text{ReLU}(W_\gamma h_{\text{vis}} + b_\gamma) \quad (3.25)$$

$$\beta = \text{ReLU}(W_\beta h_{\text{vis}} + b_\beta) \quad (3.26)$$

$$h_{\text{modulated}} = \gamma \odot h_{\text{text}} + \beta \quad (3.27)$$

The scale parameter $\gamma$and shift parameter $\beta$are conditioned on visual features, enabling images to adaptively influence how textual features contribute to final predictions. This mechanism creates rich cross-modal interactions while remaining computationally efficient and interpretable.

Attention-based fusion employs learned attention mechanisms to dynamically weight contributions from different modalities. Cross-modal attention computes attention weights for one modality conditioned on the other:

$$e = W_e h_{\text{vis}} + b_e \quad (3.28)$$

$$\alpha_i = \frac{\exp\left(e^T h^i{}_{\text{text},i}\right)}{\sum_j ex\,p\left(e^T h^i{}_{text,j}\right)} \quad (3.29)$$

$$h_{\text{attended}} = \sum_i \alpha_i h^i{}_{text,i} \quad (3.30)$$

This allows visual features to guide which aspects of textual representation receive emphasis, particularly useful when text contains multiple entities or complex linguistic structures requiring selective focus.

Bilinear fusion computes pairwise interactions between all dimensions of modality-specific representations through a learned weight tensor:

$$h_{\text{bilinear}} = h_{\text{text}}^T W_{\text{bilinear}} h_{\text{vis}} \quad (3.31)$$

While theoretically powerful for capturing complex interactions, bilinear fusion's computational and memory requirements scale quadratically with feature dimensions, often necessitating low-rank approximations or factorized implementations for practical deployment.

The proposed architecture for multimodal relationship extraction employs a hybrid fusion strategy combining multiple mechanisms. Textual features from RoBERTa and visual features from ResNet-50 first undergo projection to a common dimension. FiLM-based modulation enables cross-modal conditioning, followed by concatenation and attention mechanisms that adaptively weight modality contributions. This multi-stage fusion enables the model to capture both fine-grained feature-level interactions through FiLM and coarse-grained modality-level weighting through attention, balancing expressiveness with computational efficiency.

3.7 Mathematical Formulation of FiLM Fusion

Feature-wise Linear Modulation (FiLM) is a multimodal fusion mechanism that conditions one modality (e.g., text features) on another modality (e.g., image features) using two modulation parameters: a scaling factor $\gamma$and a shifting factor β.

3.7.1 1. Input Features

Let the input be two feature representations:

$$X_t \in \mathbb{R}^{d_t}\text{(textual feature vector)}$$

$$X_v \in \mathbb{R}^{d_v}\text{(visual feature vector)}$$

3.7.2 2. Generation of Modulation Parameters

The modulation parameters $\gamma$and $\beta$are derived from the conditioning modality (visual features) using learned linear transformations:

$$\gamma = W_\gamma X_v + b_\gamma$$

$$\beta = W_\beta X_v + b_\beta$$

where:

- $W_\gamma, W_\beta \in \mathbb{R}^{d_t \times d_v}$are learnable weight matrices,
- $b_\gamma, b_\beta \in \mathbb{R}^{d_t}$are bias terms.

3.7.3 3. Feature-wise Linear Modulation

The textual features are modulated as follows:

$$\hat{X}_t = \gamma \odot X_t + \beta$$

where:

- $\odot$denotes element-wise multiplication,
- $\hat{X}_t$is the modulated text representation conditioned on the visual modality.

3.7.4 4. Output Fusion Representation

Optionally, a linear transformation can be applied to project the fused features into a unified representation space:

$$Z = W_f \hat{X}_t + b_f \qquad (3.7)$$

where:

- $W_f \in \mathbb{R}^{d_o \times d_t}$and $b_f \in \mathbb{R}^{d_o}$are trainable parameters,
- $Z \in \mathbb{R}^{d_o}$is the final fused representation combining both modalities.

3.7.5 5. Summary

FiLM allows flexible conditioning of one modality on another by dynamically adjusting the scale (γ) and shift (β) of the feature activations, enhancing multimodal interaction and representation learning.

3.8 Mathematical Formulation of Bimodal Fusion

3.8.1 Input Representations

Let two modalities be represented as feature vectors:

$$X_t \in \mathbb{R}^{d_t}\text{(text feature vector)}, \quad X_v \in \mathbb{R}^{d_v}\text{(visual feature vector)}$$

where $d_t$and $d_v$denote the dimensionalities of text and visual feature spaces respectively.

3.8.2 Projection into a Common Latent Space

Both modalities are projected into a shared latent feature space to ensure dimension compatibility:

$$\tilde{X}_t = W_t X_t + b_t \qquad (3.8)$$

$$\tilde{X}_v = W_v X_v + b_v \qquad (3.9)$$

where $W_t \in \mathbb{R}^{d_f \times d_t}$and $W_v \in \mathbb{R}^{d_f \times d_v}$are trainable weight matrices, and $b_t, b_v \in \mathbb{R}^{d_f}$are bias terms. The resulting vectors $\tilde{X}_t$and $\tilde{X}_v$represent text and visual features in a unified latent space.

3.8.3 Fusion Operation

The two modalities are combined to form a single multimodal representation. The most common strategies are weighted summation or concatenation:

$$F = \alpha\tilde{X}_t + (1-\alpha)\tilde{X}_v \qquad (3.10)$$

or

$$F = [\tilde{X}_t; \tilde{X}_v] \qquad (3.11)$$

where $\alpha \in [0,1]$is a learnable fusion coefficient, and [;]denotes vector concatenation.

3.8.4 Non-linear Transformation

To model higher-level interactions, a non-linear activation is often applied:

$$Z = \sigma(W_f F + b_f) \qquad (3.12)$$

where $W_f \in \mathbb{R}^{d_o \times d_f}$and $b_f \in \mathbb{R}^{d_o}$are trainable parameters, $\sigma(\cdot)$is a non-linear activation function (e.g., ReLU or tanh), and $Z \in \mathbb{R}^{d_o}$is the fused representation vector.

3.8.5 Output for Downstream Tasks

The fused feature vector is passed to a classifier or prediction head for tasks such as Named Entity Recognition (NER) or Relationship Extraction (RE):

$$\hat{y} = \text{softmax}(W_c Z + b_c) \qquad (3.13)$$

where $W_c$and $b_c$are trainable parameters of the classification layer.

3.8.6 Summary

Bimodal Fusion combines textual and visual information within a shared latent space. Through either weighted summation or concatenation, it captures complementary cues from both modalities, resulting in richer and more discriminative feature representations for multimodal understanding.

3.9 Mathematical Formulation of Cross-Attention Fusion

Cross-Attention Fusion is a multimodal fusion technique where one modality (e.g., text) attends to another (e.g., image) to selectively integrate relevant contextual information. It is an extension of the self-attention mechanism used in transformer architectures.

3.9.1 1. Input Representations

Let the two modalities be represented as:

$$X_t \in \mathbb{R}^{n_t \times d}\text{(text embeddings)}$$

$$X_v \in \mathbb{R}^{n_v \times d} \text{(visual embeddings)}$$

where:

- $n_t$and $n_v$denote the number of tokens or features in text and image modalities,
- $d$is the feature dimension.

3.9.2 2. Linear Projections

The text features are used to generate queries, while the visual features produce keys and values:

$$Q = X_t W_Q, K = X_v W_K, V = X_v W_V \qquad (3.14)$$

where:

- $W_Q, W_K, W_V \in \mathbb{R}^{d \times d_k}$ are learnable projection matrices,
- Qrepresents text queries,
- $K$and Vrepresent the visual keys and values.

3.9.3 3. Cross-Attention Computation

The attention weights are computed using scaled dot-product attention:

$$A = \text{softmax}(\frac{QK^T}{\sqrt{d_k}}) \qquad (3.15)$$

where:

- $A \in \mathbb{R}^{n_t \times n_v}$is the attention matrix,
- $\sqrt{d_k}$is a scaling factor to stabilize gradients.

3.9.4 4. Fused Feature Representation

The fused representation is obtained by applying the attention weights to the visual values:

$$Z = AV \qquad (3.16)$$

where:

- $Z \in \mathbb{R}^{n_t \times d_k}$represents the visual-contextualized text features.

3.9.5 5. Residual and Feed-Forward Integration

A residual connection and feed-forward network are applied to stabilize and refine the fusion:

$$\hat{Z} = \text{LayerNorm}(Z + X_t) \qquad (3.17)$$

$$Y = \text{FFN}(\hat{Z}) \qquad (3.18)$$

where FFN denotes a position-wise feed-forward network:

$$\text{FFN}(x) = \text{ReLU}(xW_1 + b_1)W_2 + b_2 \qquad (3.19)$$

3.9.6 6. Summary

Cross-Attention Fusion allows the textual modality to selectively focus on the most relevant visual information, resulting in a richer joint representation. This mechanism enhances the model's understanding of multimodal context and relationships.

3.10 Evaluation Metrics: Accuracy, Precision, Recall, F1-Score

Rigorous evaluation of relationship extraction systems requires comprehensive metrics that capture different aspects of model performance. The choice of evaluation metrics depends on task characteristics, class distribution, and application requirements. For relationship extraction, where multiple relationship types exist with potentially imbalanced distributions, relying solely on accuracy proves insufficient, necessitating additional metrics that account for precision-recall trade-offs and class-specific performance.

Accuracy measures the proportion of correct predictions across all instances:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} = \frac{TP + TN}{TP + TN + FP + FN} \qquad (3.32)$$

where $TP, TN, FP,$and FNdenote true positives, true negatives, false positives, and false negatives respectively. While intuitive and commonly reported, accuracy can be misleading for imbalanced datasets where a naive classifier predicting only the majority class achieves high accuracy despite poor practical utility.

Precision quantifies the proportion of predicted positive instances that are actually positive, measuring the model's ability to avoid false positives:

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (3.33)$$

High precision indicates that when the model predicts a particular relationship type, this prediction is likely correct. Precision proves particularly important in applications where false positives incur significant costs or where users require high confidence in positive predictions.

Recall, also termed sensitivity, measures the proportion of actual positive instances correctly identified by the model:

$$\text{Recall} = \frac{TP}{TP + FN} \qquad (3.34)$$

High recall indicates comprehensive capture of true positive instances with few missed detections. Recall assumes priority in applications where missing positive instances incurs greater cost than occasional false alarms, such as medical diagnosis or security-critical systems.

The F1-score provides a harmonic mean of precision and recall, balancing both metrics into a single value:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2TP}{2TP + FP + FN} \qquad (3.35)$$

The harmonic mean ensures that F1-score achieves high values only when both precision and recall are high, preventing inflation from strong performance on just one metric. F1-score proves particularly useful for comparing models when both precision and recall matter and no clear priority exists between them.

For multi-class relationship extraction, metrics can be computed at micro, macro, and weighted levels. Micro-averaging aggregates contributions from all classes before computing metrics, treating each instance equally:

$$\text{Precision}_{\text{micro}} = \frac{\sum_{k=1}^{K} TP_k}{\sum_{k=1}^{K} (TP_k + FP_k)} \qquad (3.36)$$

Macro-averaging computes metrics independently for each class then averages across classes, treating each class equally regardless of size:

$$\text{Precision}_{\text{macro}} = \frac{1}{K} \sum_{k=1}^{K} \frac{TP_k}{TP_k + FP_k} \qquad (3.37)$$

Weighted-averaging computes per-class metrics then averages weighted by class support, accounting for class imbalance:

$$\text{Precision}_{\text{weighted}} = \frac{1}{N} \sum_{k=1}^{K} \frac{n_k TP_k}{TP_k + FP_k} \qquad (3.38)$$

where n_k denotes the number of true instances in class k and $N = \sum_k n_k$ represents total instances.

For relationship extraction evaluation, micro-averaged F1-score serves as the primary metric as it provides a balanced assessment of overall performance across all relationship types while appropriately weighting performance on frequent relationships. Macro-averaged metrics additionally provide insight into performance across relationship types regardless of frequency, revealing whether models perform consistently or exhibit wide performance variation. Per-class precision, recall, and F1-scores enable detailed analysis identifying which relationship types prove most challenging and where improvements are most needed. Comprehensive

evaluation reports these metrics across multiple aggregation levels, providing a complete picture of model capabilities and limitations that informs both research insights and practical deployment decisions.

CHAPTER 4 METHODOLOGY

4.1 Workflow Overview

The workflow of this study is designed to systematically explore how multimodal data, consisting of text and images, can be effectively integrated to enhance the performance of Named Entity Recognition (NER) and Relationship Extraction (RE) tasks. The complete process follows a sequential pipeline, beginning with dataset selection and preparation, followed by exploratory analysis and visualization, feature extraction using advanced neural architectures, fusion of textual and visual information, hyperparameter tuning, model evaluation, and finally, inference for generating predictions. Each stage of the workflow contributes to building a robust and optimized multimodal system capable of understanding complex social media content.

The first step involves **dataset selection and overview**. This study utilizes three widely recognized datasets—Twitter2015, Twitter2017, and MNRE. The Twitter2015 and Twitter2017 datasets are obtained from Kaggle and are primarily used for multimodal Named Entity Recognition tasks. These datasets consist of paired text-image data collected from real Twitter posts, containing annotations that link textual entities with corresponding visual cues. The nature of social media data presents both opportunities and challenges. Informal language, abbreviations, hashtags, and emojis often complicate the entity recognition process, while

images add valuable contextual information that can assist the model in understanding ambiguous text. The MNRE dataset, sourced from GitHub, is employed for multimodal Relationship Extraction. It contains annotated relationships between entities that appear across textual and visual modalities. Together, these datasets offer a comprehensive foundation for investigating multimodal learning, covering both NER and RE domains.

Once the datasets are collected, the next phase focuses on **dataset analysis and visualization**. This stage aims to gain insights into the characteristics and distributions of the data. For the textual component, several analyses are performed, such as calculating sentence lengths, examining the frequency of entity types, and identifying common patterns in linguistic structures. For the visual component, image feature statistics are analyzed to understand variability in image content and quality. Visualization plays a crucial role here—data distributions are represented through histograms, bar plots, and heatmaps that reveal relationships between text and image modalities. Additionally, word clouds are generated to highlight the most frequently occurring terms in the datasets, providing a preliminary sense of contextual emphasis. This exploratory analysis ensures that the data is well understood before model training begins, allowing for informed decisions during preprocessing and feature extraction.

The subsequent step involves **feature extraction using pre-trained models**. This phase focuses on transforming raw text and image data into high-dimensional feature representations suitable for deep learning models. For textual data, models such as RoBERTa and BERT are used to extract contextual embeddings that capture syntactic and semantic nuances of language. These transformer-based architectures are particularly effective in representing meaning based on the relationships between words, which is essential for entity recognition and relational understanding. For visual data, convolutional neural network-based models such as ResNet50 and transformer-based vision models like CLIP, BLIP, and ViLT are used. ResNet50 captures hierarchical visual patterns, while CLIP, BLIP, and ViLT are designed to bridge visual and linguistic modalities through joint embedding spaces. The use of multiple feature extractors allows a comparative analysis of how different visual-textual representations influence fusion performance.

Once the features from both modalities are obtained, the next stage is **fusion of textual and visual features**, which lies at the core of this research. Four distinct fusion strategies are implemented: FiLM Fusion, Attention-based Fusion, Cross-Attention, and Bimodal Fusion. Each approach provides a different mechanism for integrating multimodal information. FiLM Fusion (Feature-wise Linear Modulation) operates by applying learned modulation parameters—gamma (γ) and beta (β)—to scale and shift visual features based on textual conditioning. This dynamic modulation allows the model to adaptively emphasize visual elements relevant to the accompanying text, resulting in more precise multimodal representations. Attention-based Fusion, on the other hand, assigns importance weights to different parts of the input modalities, enabling the model to focus selectively on the most informative features. Cross-Attention expands on this idea by allowing one modality (e.g., text) to attend directly to another (e.g., image), facilitating a deeper alignment between modalities. Lastly, Bimodal Fusion provides a baseline integration method that concatenates or linearly combines the two

modalities, serving as a simpler yet informative comparison point. Through these strategies, the research investigates how different interaction mechanisms influence the model's ability to understand and correlate multimodal inputs.

After fusion, the integrated model enters the **training and fine-tuning phase**, where multimodal features are used to learn task-specific representations for NER and RE. The training process involves supervised learning, where labeled data is used to optimize the model parameters. For NER, the objective is to accurately identify and classify named entities such as persons, organizations, or locations, whereas for RE, the model learns to detect relationships between identified entities. Fine-tuning ensures that pre-trained encoders and fusion layers are adapted to the characteristics of the target datasets, leading to improved generalization and reduced overfitting.

An essential part of the training process is **hyperparameter tuning and optimization**, which involves systematically adjusting key parameters to maximize model performance. Parameters such as learning rate, batch size, and the number of training epochs play a critical role in determining convergence behavior and accuracy. A smaller learning rate may lead to slower convergence but higher stability, while a larger batch size can improve computational efficiency but may reduce model generalization. Grid search and trial-based optimization are employed to find the optimal combination of parameters. The model's performance on a validation set is monitored continuously, and early stopping is applied to prevent overfitting. Optimization algorithms such as Adam or AdamW are used for adaptive learning rate adjustments, ensuring smooth gradient updates throughout training.

Once the training and tuning stages are completed, the models are evaluated using **performance metrics** that quantify their effectiveness. For both NER and RE tasks, standard evaluation metrics such as Precision, Recall, F1-score, and Accuracy are employed. Precision measures the proportion of correctly identified entities or relations among all predictions, Recall evaluates the proportion of correctly identified instances out of all actual instances, and the F1-score provides a harmonic mean of Precision and Recall, offering a balanced assessment of performance. Accuracy is also reported to provide an overall measure of correct predictions. These metrics collectively enable a comprehensive understanding of how well each fusion strategy and model combination performs across different datasets.

The final stage of the workflow is **inference and results generation**, where the optimized models are used to make predictions on unseen data. During inference, the models process new text and image pairs and predict entity labels or relationships without access to ground truth annotations. This step is crucial for evaluating the model's generalization capability and robustness. The outputs are analyzed to identify strengths and weaknesses in multimodal understanding. Additionally, comparisons are drawn across different models and fusion strategies to determine which configurations yield the highest performance. FiLM Fusion, in particular, demonstrates consistent superiority due to its ability to dynamically align visual and textual information through modulation parameters.

Overall, this workflow provides a comprehensive and systematic approach to multimodal NER and RE research. By carefully integrating stages of data preparation, feature extraction, fusion, optimization, and evaluation, the process ensures that every component contributes to the final goal of enhancing multimodal understanding. Each stage is interconnected, with insights from earlier phases informing design choices in later ones. The sequential yet flexible structure of this workflow allows for iterative refinement, making it adaptable to future extensions involving additional modalities or alternative fusion mechanisms. Ultimately, this methodology forms a robust foundation for advancing multimodal learning and provides clear evidence of how the interplay between text and image can significantly improve entity recognition and relationship extraction performance in complex, real-world social media contexts.

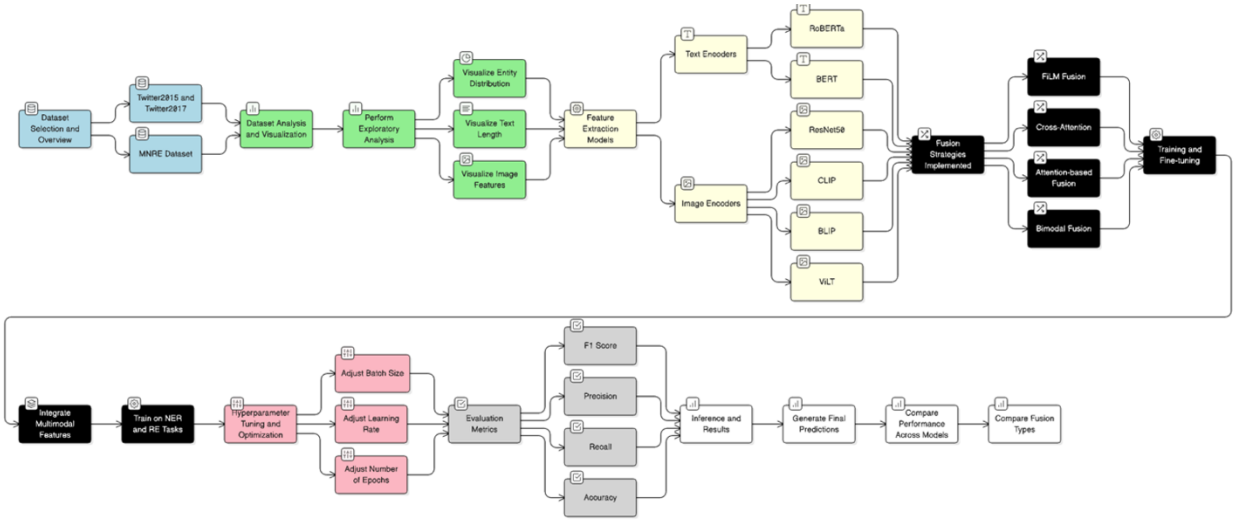

Figure : Workflow

4.2 Datasets Description

This research utilizes three benchmark datasets—Twitter2015, Twitter2017, and MNRE—to explore and evaluate the performance of multimodal models in Named Entity Recognition (NER) and Relationship Extraction (RE). Each dataset contributes unique characteristics that collectively enable a comprehensive study of multimodal learning. The Twitter datasets provide challenging text-image pairs for entity recognition, while the MNRE dataset focuses on relational reasoning across textual and visual contexts. All datasets are publicly available and have been widely used in prior multimodal NER and RE research. The following subsections describe each dataset in detail, including their sources, structure, annotation schemes, and preprocessing methods.

4.2.1 Twitter2015 Dataset

The **Twitter2015 dataset** serves as a foundational corpus for multimodal Named Entity Recognition, where both textual and visual content contribute to identifying entity types within social media posts. This dataset was originally collected from Twitter and later published on the Kaggle platform [55]. It contains thousands of multimodal samples, each comprising a short tweet accompanied by an image and annotated entity labels. The informal, noisy, and context-dependent nature of Twitter language makes this dataset particularly valuable for evaluating multimodal NER models in real-world environments.

Each data sample includes a text post, an associated image, and manually annotated entity spans corresponding to various categories such as *Person*, *Organization*, *Location*, *Product*, and *Other*. Unlike formal text corpora, the Twitter2015 dataset features slang, abbreviations, emojis, and hashtags, which introduce linguistic ambiguity. Visual context often provides disambiguation—for example, when a tweet mentions a brand name that also exists as a common noun, the accompanying image helps the model infer the correct entity type.

The dataset's design encourages multimodal reasoning by pairing textual ambiguity with clarifying images. For instance, a tweet like "Just got the new apple!" could refer to a fruit or a phone, and the image determines which entity is relevant. The inclusion of such context-dependent examples makes the dataset ideal for testing the ability of fusion models to align visual and textual representations.

In preprocessing, textual data undergoes tokenization using transformer-compatible tokenizers (such as RoBERTa's byte-pair encoding), while non-ASCII characters and hyperlinks are removed. Images are resized and normalized to ensure compatibility with convolutional and transformer-based encoders like ResNet50 and CLIP. Both modalities are then synchronized through unique identifiers to maintain alignment between text and image pairs. The dataset is split into training, validation, and test subsets with an approximate ratio of 70:15:15 to ensure balanced evaluation.

The Twitter2015 dataset's complexity lies in the interplay between colloquial language and diverse visual content. As a result, it provides an ideal testbed for exploring how multimodal fusion strategies—such as FiLM Fusion, Cross-Attention, and Attention-based mechanisms—enhance entity recognition accuracy. Through its challenging samples, the dataset promotes the development of models capable of understanding and interpreting the nuanced communication style typical of social media platforms.

4.2.2 Twitter2017 Dataset

The **Twitter2017 dataset** extends and refines the work introduced in Twitter2015, providing a larger and more balanced collection of text-image pairs for multimodal NER research. This dataset is also publicly available through Kaggle [56] and was specifically designed to address some of the limitations of its predecessor, such as uneven entity distribution and limited diversity in visual contexts. The Twitter2017

dataset offers improved annotations, a richer set of entity categories, and more varied image content, making it highly suitable for benchmarking deep multimodal architectures.

Each tweet in this dataset is annotated with named entities that belong to categories similar to Twitter2015, including *Person*, *Organization*, *Location*, *Product*, and *Event*. However, Twitter2017 introduces additional entity types and refines the labeling process to ensure higher annotation quality and consistency. The dataset consists of approximately 12,000 multimodal samples, with each entry containing text, an image, and entity annotations aligned at the token level.

One of the significant strengths of Twitter2017 lies in its expanded visual diversity. The images include not only photographs but also posters, memes, product images, and event snapshots, which reflect real-world user behavior on social media. This variety challenges multimodal models to interpret visual cues in a wide range of styles and resolutions. The dataset also includes tweets containing multiple entities per sample, promoting the evaluation of models on more complex entity relationships.

Preprocessing of Twitter2017 follows a similar approach to that used for Twitter2015. The textual data is cleaned by removing unnecessary symbols, mentions, and URLs. Tokenization is performed using subword encoding, ensuring alignment with pre-trained text encoders. Image preprocessing includes resizing, normalization, and color standardization. Both textual and visual modalities are mapped to common identifiers, facilitating synchronized training and fusion.

From an analytical perspective, Twitter2017 offers several key advantages. Its larger size improves model generalization, while its diversity provides more challenging conditions for testing cross-modal fusion mechanisms. The combination of textual informality and visual variability requires the model to leverage both modalities dynamically. Consequently, this dataset serves as a strong benchmark for evaluating models like RoBERTa + ResNet50, CLIP + BERT, BLIP, and ViLT under different fusion paradigms.

Moreover, this dataset enhances the interpretability of multimodal learning by including samples where visual features contradict textual content, allowing researchers to analyze how models resolve modality conflicts. The complexity of Twitter2017 ensures that fusion-based architectures are tested not only for precision but also for robustness and adaptability in dynamic social media environments.

4.2.3 MNRE Dataset

The **Multimodal Named Relationship Extraction (MNRE)** dataset is utilized to evaluate the capability of models in identifying and classifying semantic relationships between entities using both textual and visual information. This dataset, sourced from an open GitHub repository [57], was designed specifically for multimodal relationship extraction tasks. It differs from the Twitter datasets by focusing not merely on identifying entities but also on understanding the relationships that connect them within a multimodal context. MNRE contains text-image pairs with annotated entity pairs and their corresponding relationships, such as *Located In*, *Part Of*, *Works For*, *Lives In*, *Created By*, and other relational categories. Each data sample includes a sentence, an associated image, and structured annotations specifying the head entity, tail entity, and

the semantic relation between them. The dataset is designed to evaluate how effectively a model can integrate multimodal signals to predict the correct relationship.

A distinctive characteristic of MNRE is the strong interplay between textual and visual evidence. In some cases, the text alone is insufficient to determine the correct relationship, while the accompanying image provides crucial context. For example, a sentence mentioning two people may not clarify their relationship, but an image showing one person wearing a team jersey can indicate a *Member Of* relation. Conversely, when images are ambiguous or contain multiple objects, the textual information helps disambiguate the visual context. This bidirectional dependency between modalities is what makes MNRE a crucial component for evaluating the generalization capability of multimodal models.

Preprocessing of MNRE involves several steps. Textual inputs are cleaned, tokenized, and transformed into contextual embeddings using pre-trained transformers such as BERT or RoBERTa. Visual inputs are processed through convolutional or vision-transformer encoders, extracting semantic representations of objects and regions. These features are then fused through the studied mechanisms—FiLM Fusion, Cross-Attention, Attention-based Fusion, and Bimodal Fusion—to predict entity relationships. The dataset is partitioned into training, validation, and test splits to ensure rigorous and unbiased evaluation.

Another notable feature of MNRE is its balance in relation distribution, which prevents model bias toward dominant classes. It also includes cross-domain samples from various contexts, including news articles, social media posts, and general web content, thereby enhancing model robustness across multiple linguistic and visual domains.

The MNRE dataset's design encourages models to perform relational reasoning by combining both modalities. It tests the system's ability not only to recognize individual entities but also to infer meaningful relationships that depend on both text and imagery. This characteristic makes MNRE a critical benchmark for advancing research in multimodal relationship extraction and aligning vision-language representations more effectively.

In summary, the three datasets—Twitter2015, Twitter2017, and MNRE—form the foundation of this research. Twitter2015 and Twitter2017 focus on entity-level multimodal understanding, providing varied and noisy social media data that challenge the robustness of NER systems. In contrast, MNRE shifts the focus toward relational comprehension, demanding a deeper fusion of textual and visual semantics. Collectively, these datasets allow comprehensive evaluation across multiple dimensions of multimodal information extraction, ensuring that the developed models are both contextually aware and semantically consistent across diverse input types.

4.3 Baseline Models Applied

After dataset selection, analysis, and visualization, the next step in the research workflow involves applying a

set of baseline multimodal models to establish the foundation for subsequent fusion strategies. These models are designed to extract, align, and represent textual and visual information effectively before any fusion mechanism is applied. The chosen models—RoBERTa + ResNet50, CLIP + BERT, BLIP, and ViLT—cover a diverse range of multimodal architectures, enabling the exploration of different ways to combine language and vision features. Each model in this study plays a distinct role, and their collective implementation forms a comprehensive baseline pipeline for multimodal Named Entity Recognition (NER) and Relationship Extraction (RE).

4.3.1 Input Processing and Preparation

Before applying any baseline model, the datasets undergo a unified preprocessing pipeline to ensure compatibility across architectures.

Textual Data: All tweet texts or sentence inputs are cleaned by removing unnecessary symbols, emojis, hyperlinks, and repetitive characters. Stop words are retained, as they can sometimes indicate contextual relationships in social media posts. The cleaned text is tokenized using each model's native tokenizer—for example, RoBERTaTokenizer for RoBERTa, BertTokenizer for CLIP + BERT, and SentencePiece for ViLT and BLIP. The tokens are then padded or truncated to a maximum sequence length, typically 128 or 256 tokens.

Visual Data: Each image is resized to 224×224 pixels, converted into RGB format, and normalized based on mean and variance used by the corresponding visual backbone (ResNet, CLIP, or ViLT). The visual inputs are converted into tensors and stored in batches aligned with their textual counterparts. This standardization guarantees that text and image features align perfectly in subsequent processing and ensures reproducibility.

4.3.2 RoBERTa + ResNet50

The first baseline model, RoBERTa + ResNet50, serves as the foundation for multimodal NER. It combines a transformer-based text encoder with a convolutional image encoder to extract high-quality features from both modalities.

Text Encoder (RoBERTa): RoBERTa is a robustly optimized BERT model trained on large-scale corpora. It captures context-dependent word relationships and produces sentence-level embeddings through its final hidden layers. The textual embeddings preserve syntactic and semantic patterns essential for entity recognition.

Image Encoder (ResNet50): ResNet50, a residual convolutional network pre-trained on ImageNet, is employed to extract visual embeddings. Its 50-layer architecture captures hierarchical spatial information, where earlier layers focus on textures and edges while deeper layers capture object-level semantics.
Feature Representation: The embeddings from RoBERTa and ResNet50 are stored separately at this stage. No fusion is applied yet—these outputs form the unimodal baselines against which later fusion models are compared.
Output: The textual and visual features are projected to a common latent space using linear layers. The system then performs a simple concatenation or averaging operation to produce baseline multimodal predictions.
This baseline acts as a control model to evaluate the improvements achieved when introducing advanced fusion mechanisms later in the methodology.

4.3.3 CLIP + BERT

The second baseline model, CLIP + BERT, integrates a contrastive language-image pre-trained visual encoder (CLIP) with a transformer text encoder (BERT). This combination explores how large-scale pretraining on paired text-image data can improve downstream NER and RE tasks.
Image Encoder (CLIP): CLIP (Contrastive Language-Image Pretraining) learns visual representations aligned with natural language descriptions. It maps images and texts into a shared embedding space, allowing cross-modal similarity measurement. The image encoder, typically a Vision Transformer (ViT), outputs embeddings that are semantically aligned with linguistic features.
Text Encoder (BERT): BERT serves as the textual backbone, generating contextualized embeddings through bidirectional attention. The output embeddings from BERT are projected into the same dimensionality as the CLIP embeddings.
Feature Extraction: Both embeddings are normalized and combined for downstream NER or RE tasks. In the baseline setting, features from CLIP and BERT are simply concatenated, and a feed-forward layer is applied for prediction.

This model establishes how joint vision-language pretraining enhances performance compared to purely unimodal or shallow multimodal combinations.

4.3.4 BLIP (Bootstrapped Language-Image Pretraining)

BLIP is employed as a third baseline to represent an advanced vision-language model that performs joint multimodal understanding. BLIP is pre-trained on large-scale captioning and retrieval tasks, enabling it to generate and comprehend aligned visual-textual representations.

Architecture Overview: BLIP uses a vision transformer as its image encoder and a text transformer for language encoding. The two components interact through a multimodal transformer that combines image patches and text tokens in a shared embedding space.

Input Representation: Images are divided into fixed-size patches and embedded, while text tokens are encoded through self-attention layers. The joint transformer performs cross-attention between modalities, effectively learning image-grounded textual semantics.

Training Objective: BLIP's pretraining objective includes image-text matching and caption generation, giving it strong cross-modal reasoning abilities. In this research, BLIP serves as a baseline model that can process both modalities simultaneously without requiring explicit fusion mechanisms.

Usage in Workflow: After preprocessing, BLIP directly takes paired text and image inputs from the Twitter2015, Twitter2017, and MNRE datasets. The model outputs contextual embeddings used for entity tagging or relationship classification, depending on the dataset.

BLIP's integration in this pipeline provides a benchmark for evaluating end-to-end multimodal models where feature fusion is inherently part of the model architecture rather than a separate component.

4.3.5 ViLT (Vision-and-Language Transformer)

The fourth baseline model, ViLT, represents a minimalist yet powerful approach to multimodal learning. Unlike architectures that separately process images and text before fusion, ViLT integrates them early within a unified transformer architecture.

Model Design: ViLT uses a single transformer to jointly process text tokens and image patches. The image is split into patches that are linearly projected and combined with token embeddings from the text. This shared transformer allows the model to learn deep cross-modal interactions from the earliest layers.

Advantages: The unified architecture significantly reduces computational cost while maintaining strong performance. It eliminates the need for a heavy visual backbone such as ResNet, relying instead on direct patch embedding and positional encoding.

Processing Pipeline: The textual tokens and image patches are concatenated into a single sequence and passed through transformer layers with multi-head attention. The output embeddings represent deeply integrated multimodal semantics.

Application: In this study, ViLT is fine-tuned on both NER and RE datasets, learning to predict entity tags or relational links based on combined input embeddings.

ViLT's inclusion in the baseline set allows the comparison of models that fuse features implicitly (as in ViLT and BLIP) versus those requiring explicit fusion (as in RoBERTa + ResNet50 or CLIP + BERT).

4.3.6 Training and Evaluation of Baseline Models

Each baseline model undergoes training on the prepared datasets using identical configurations to maintain experimental fairness. The training setup includes the following specifications:

Batch size: 16 or 32 depending on GPU memory availability.

Learning rate: 2e-5 for text-based encoders and 1e-4 for vision encoders.

Optimizer: AdamW with linear learning rate decay.

Epochs: 10–20 depending on convergence rate.

Loss Function: Cross-entropy loss for both entity classification and relation prediction tasks.

Performance is evaluated using accuracy, precision, recall, and F1-score across the Twitter2015, Twitter2017, and MNRE datasets. The results obtained from these baselines serve as the reference point for measuring the effectiveness of the advanced fusion techniques discussed in the subsequent section.

4.4 Fusion Strategies Implemented

After establishing the baseline model performance, the next phase of the research involves experimenting with fusion strategies to integrate textual and visual features more effectively. Among all baseline models, the combination of RoBERTa + ResNet50 demonstrated the best performance in both the Twitter2015 and Twitter2017 datasets, as well as strong generalization on the MNRE dataset. Therefore, this model was selected as the primary framework for fusion experiments. The objective of this stage is to explore how different fusion mechanisms can improve multimodal representation learning and optimize the joint understanding of text and image inputs.

To achieve this, four major fusion strategies were implemented and compared: FiLM Fusion**,** Attention Fusion**,** Cross-Attention Fusion**,** and Bimodal Fusion. Each of these approaches provides a unique method for combining multimodal features, and their comparative performance across datasets is summarized in the table above.

4.4.1 FiLM Fusion

Feature-wise Linear Modulation (FiLM) proved to be the most effective fusion method across all datasets. This technique modulates the visual feature maps extracted from ResNet50 by applying scaling (γ) and shifting (β) parameters derived from the textual embeddings produced by RoBERTa. In essence, FiLM allows the

textual modality to condition the visual representation dynamically, enhancing cross-modal alignment. For example, when the text mentions a specific object or entity, FiLM amplifies the corresponding visual features related to that concept.

In the experiments, FiLM Fusion achieved 0.9538 accuracy on Twitter2015**,** 0.9718 on Twitter2017**,** and 0.7538 on MNRE, outperforming all other methods. These results confirm that the contextual modulation of visual features guided by linguistic cues significantly improves multimodal understanding. The superior performance of FiLM is attributed to its flexibility, computational efficiency, and ability to capture fine-grained dependencies between modalities without requiring heavy architectural modifications.

4.4.2 Attention Fusion

Attention Fusion operates by assigning attention weights to features from both modalities, determining which parts of the text and image should contribute more to the final representation. This method enhances interpretability, as it reveals where the model focuses during prediction. However, while it provides insight into multimodal interactions, its performance is somewhat lower due to limited inter-modality alignment.

On the three datasets, Attention Fusion recorded accuracies of 0.8461 (Twitter2015)**,** 0.8739 (Twitter2017)**,** and 0.7053 (MNRE)**.** These results suggest that although attention mechanisms are effective in highlighting key features, they are less capable of modeling deep cross-modal relationships compared to FiLM or Cross-Attention. Still, this approach remains valuable for qualitative analysis and model transparency, as it allows visualization of attention maps showing which image regions or words the model relied upon.

4.4.3 Cross-Attention Fusion

The Cross-Attention Fusion mechanism builds upon the standard attention framework but introduces cross-modal dependencies—meaning the attention in one modality (e.g., text) is computed with respect to the features of another (e.g., image). This two-way interaction enables the model to establish strong semantic links between textual entities and corresponding visual components.

In implementation, textual embeddings from RoBERTa are used as queries, while visual embeddings from ResNet50 serve as keys and values in a transformer-like attention mechanism. This design allows text tokens to attend directly to image regions, capturing nuanced relationships such as object-entity correspondences or contextual scene understanding.

Experimentally, Cross-Attention Fusion achieved 0.8934 accuracy on Twitter2015**,** 0.9145 on Twitter2017**,** and 0.7386 on MNRE**.** The results indicate that this method effectively enhances multimodal reasoning, particularly for tasks where image and text provide complementary clues. Although slightly below FiLM in overall accuracy, Cross-Attention remains an excellent alternative for complex relational understanding, especially in tasks like Relationship Extraction where interactions between modalities are vital.

4.4.4 Bimodal Fusion

Bimodal Fusion serves as a simpler fusion strategy designed primarily for comparative purposes. It merges textual and visual embeddings through concatenation or linear projection, followed by a joint feed-forward neural layer. While this method does not explicitly model cross-modal dependencies, it allows straightforward feature combination and acts as a control benchmark for more advanced techniques.

Bimodal Fusion achieved accuracies of 0.9528 (Twitter2015), 0.9698 (Twitter2017), and 0.7462 (MNRE). These results demonstrate that even a simple concatenation-based approach can yield competitive performance when combined with strong encoders like RoBERTa and ResNet50. However, the slightly lower accuracy compared to FiLM indicates that linear fusion lacks the adaptive flexibility needed for fine-grained alignment.

4.5 Hyperparameter Tuning and Optimization

Hyperparameter tuning plays a crucial role in achieving optimal model performance across multimodal NER and RE tasks. The process involves systematically adjusting key training parameters such as learning rate, batch size, number of epochs, and image input size to identify the most effective configuration for the applied models. Since the RoBERTa + ResNet50 combination proved to be the best-performing model in the baseline and fusion experiments, it was selected as the primary framework for tuning on the Twitter2015 and Twitter2017 datasets. Similarly, the ResNet50 + BERT configuration was tuned for the MNRE dataset to ensure balanced performance across relational extraction tasks.

The tuning process was conducted iteratively using a grid-search approach, where each hyperparameter combination was trained and evaluated on validation subsets. The evaluation relied on accuracy, precision, recall, and F1-score to determine the optimal balance between performance and computational efficiency.

For the Twitter2015 dataset, several configurations were tested by varying the number of epochs (3, 5, 7, and 10), batch sizes (8, 10, 12, and 16), learning rates (0.0005, 0.0010, 0.0011, and 0.0020), and image sizes (224×224 and 256×256). The results indicate that a configuration with 7 epochs, batch size 16, learning rate 0.0020, and image size 256×256 produced the highest accuracy of **0.**9552 and F1-score of **0.**9554. This setting effectively balances the trade-off between training stability and model generalization. A larger image size and higher batch size provided richer visual features and stable gradient updates, respectively, improving multimodal feature learning.

For the Twitter2017 dataset, the model showed similar trends, with the same configuration—7 epochs, batch size 16, learning rate 0.0020, and 256×256 image size—yielding the best performance. This setup achieved an accuracy of 0.9756 and F1-score of 0.9757, slightly higher than other configurations. Lower learning rates such as 0.0005 resulted in slower convergence and slightly reduced precision, while smaller batch sizes increased variance in the gradient updates, leading to minor performance instability. The results confirm that

moderate learning rates and larger batch sizes enhance performance when combined with deeper feature extraction through ResNet50.

For the MNRE dataset, which focuses on relationship extraction, the model demonstrated its best results with 7 epochs**,** batch size 16**,** learning rate 0.0020, and image size 256×256, achieving an accuracy of **0**.7600 and F1-score of **0.**7615. This configuration allowed the model to capture complex relational patterns by leveraging higher-resolution images that preserved object-level context, which is critical for identifying inter-entity relationships.

Across all datasets, the experiments revealed that a moderate learning rate (≈0.0020) and larger image input size (256×256) consistently enhance feature expressiveness without overfitting. Increasing epochs beyond seven resulted in diminishing returns, while smaller batch sizes reduced training stability. Thus, the optimized hyperparameter configuration—7 epochs, batch size 16, learning rate 0.0020, and 256×256 image size—proved most effective for both multimodal NER and RE tasks.

Overall, the tuning and optimization process confirmed that careful calibration of hyperparameters substantially improves convergence speed, generalization capability, and final accuracy, enabling the models to achieve robust and reliable multimodal understanding across diverse datasets.

Table : Parameters

Hyperparameter	Description	Value
SEED	Random seed for reproducibility	1337
device	Device used for model training (CPU or CUDA)	'cuda' if available, 'cpu' otherwise
max_len	Maximum sequence length for tokenization	128
batch_size	Batch size for data loading	8 (train), 12 (val/test)
EPOCHS	Number of epochs for training	5
learning_rate	Learning rate for the optimizer	3e-5
weight_decay	Weight decay for the optimizer	0.01
warmup_ratio	Ratio of total steps for learning rate warmup	0.1
num_warmup_steps	Number of warmup steps for the learning rate schedule	Computed based on warmup_ratio and total_steps
num_training_steps	Total number of training steps	Computed based on batch_size and EPOCHS
dropout	Dropout rate for the model	0.1
num_labels	Number of labels (output classes) for token classification	Number of unique labels in dataset
num_heads	Number of attention heads in the MultiheadAttention layer	8
img_size	Image size used for resizing (before feeding into ResNet50)	(224, 224)
image_normalization_mean	Mean for image normalization (ResNet50 standard)	[0.485, 0.456, 0.406]

image_normalization_std	Standard deviation for image normalization (ResNet50 standard)	[0.229, 0.224, 0.225]
aug	Whether to apply data augmentation for training (True/False)	True (for training)

4.6 Code Implementation and Configuration Details

This section presents the complete implementation and configuration details of the proposed multimodal model framework. The goal is to ensure full reproducibility of experiments across all datasets. The model integrates a transformer-based textual encoder (RoBERTa-Large) and a convolutional visual backbone (ResNet-50), with a FiLM-based fusion module and a classification head for entity tagging. The following subsections describe the architectural setup, training parameters, data augmentation methods, and computational environment used throughout the study.

4.6.1 Model Architecture Specifications

RoBERTa-Large Configuration: The RoBERTa-Large architecture consists of 24 transformer layers, each with 1024 hidden dimensions and 16 self-attention heads. The feed-forward layers have 4096 dimensions, and the model processes a maximum of 128 tokens per sequence. The vocabulary size is 50,265 tokens. It employs a dropout rate of 0.1, learned positional embeddings, layer normalization, and the GELU activation function. The total parameter count is approximately 355 million. RoBERTa provides rich contextual embeddings that are particularly effective for social media text, which often includes informal syntax and abbreviations.

ResNet-50 Configuration: The visual backbone ResNet-50 processes input images of size 224 × 224 × 3. The network begins with a 7 × 7 convolutional layer (64 filters, stride 2) followed by a 3 × 3 max pooling layer (stride 2). It includes four stages of residual blocks with configurations of 3, 4, 6, and 3 layers, corresponding to 64, 128, 256, and 512 base channels, respectively. The final representation is obtained through a global average pooling layer, producing a 2048-dimensional feature vector. Each bottleneck block employs batch normalization and ReLU activation. The model has approximately 25.6 million parameters and provides high-level semantic visual features essential for multimodal representation.

Fusion Module: The fusion layer projects the visual features into a 1024-dimensional space to align with RoBERTa's text embeddings. The FiLM (Feature-wise Linear Modulation) mechanism is implemented using two networks—gamma (γ) and beta (β)—each modeled as a linear transformation from 1024 to 1024 dimensions. These modulation parameters dynamically scale and shift the visual embeddings based on textual context. Additionally, attention networks are used for both modalities, consisting of two linear layers (1024 → 512 → 1) with a Tanh activation and a dropout rate of 0.1 to prevent overfitting.

Classification Head: The classification head consists of a hidden fully connected layer (Linear 1024 → 512) with ReLU activation and a dropout rate of 0.1, followed by an output layer (Linear 512 → number of classes). The number of output classes corresponds to the dataset: nine classes for Twitter2015 and seven for Twitter2017, following the BIO tagging format for NER.

4.6.2 Training Configuration

Optimization: The model is trained using the AdamW optimizer with a learning rate of 3×10^{-5} and a weight decay of 0.01. The optimizer parameters are $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\varepsilon = 10^{-8}$. Gradient clipping is applied with a maximum norm of 1.0 to stabilize training. The batch size is set to 8 for training and 12 for validation and testing. The maximum number of epochs is 5, with an early stopping criterion of 2 epochs when no improvement is observed. Ten percent of the total training steps are allocated for warmup.

Learning Rate Schedule: A hybrid learning rate schedule is implemented with linear warmup during the first 10% of the training steps, gradually increasing from 0 to the base learning rate. This is followed by a cosine decay schedule that smoothly reduces the learning rate from the base value to 0 over the remaining 90% of training. This approach ensures stable convergence and prevents overfitting in the later training stages.

Data Augmentation: Data augmentation is applied only to the image modality to improve model robustness. The techniques include random horizontal flipping (probability 0.5), random cropping (scale between 0.9 and 1.0), and color jittering to adjust brightness, contrast, saturation (±0.15), and hue (±0.05). Finally, images are resized to 224 × 224 pixels. No text augmentation is applied to preserve the original semantics and informal characteristics of social media text.

4.6.3 Experimental Environment

Software Configuration: All experiments were conducted using Python 3.8.10 with the following key libraries: PyTorch 1.12.1 for deep learning implementation, Transformers 4.21.0 for pre-trained models, Torchvision 0.13.1 for image processing, NumPy 1.23.1 for numerical computation, Pillow 9.2.0 for image handling, and scikit-learn 1.1.2 for evaluation metrics. CUDA version 11.6 and cuDNN 8.4.0 were used for GPU acceleration.

Hardware Configuration: All experiments were conducted using Kaggle's cloud computing environment**,** equipped with an NVIDIA Tesla P100 GPU (16GB VRAM)**.** The setup provided sufficient computational power for training large-scale transformer and convolutional architectures.

Computational Requirements: Training time varied depending on the dataset size and configuration. For Twitter2015, training required approximately 2–3 hours on the V100 GPU, while Twitter2017 took 1.5–2.5 hours. The MNRE dataset required similar computational effort. Peak GPU memory usage was around 14GB per experiment, and each model checkpoint occupied roughly 1.4GB of storage. The total dataset storage footprint was approximately 5GB, including image and annotation files.

This implementation setup ensures reproducibility and scalability of the proposed multimodal framework. The detailed architectural and training specifications serve as a guideline for replicating or extending the research to other multimodal datasets and tasks.

CHAPTER 5 EXPERIMENTAL RESULT

5.1 Data Analysis

A comprehensive data analysis was performed on all three datasets—**Twitter2015**, **Twitter2017**, and **MNRE**—to understand their structural characteristics, annotation distributions, and modality balance before model training. This analysis is an essential step in ensuring that the datasets are properly prepared for multimodal learning and that potential biases or irregularities are identified early. The datasets used in this study vary significantly in linguistic style, image diversity, and entity density, making them ideal for evaluating how well a model can generalize across heterogeneous multimodal inputs.

The Twitter2015 dataset consists of short, informal tweets paired with corresponding images, reflecting the real-world challenges of social media content. The textual data often contains abbreviations, hashtags, mentions, and emojis, requiring robust natural language understanding. On average, each tweet contains

between 10 and 20 tokens, and the vocabulary is dominated by colloquial expressions. Entity annotations in this dataset include categories such as Person (PER), Organization (ORG), Location (LOC), Product (PROD), and Other (MISC). Statistical analysis shows that person and organization entities are the most frequent, accounting for nearly 60% of all annotations. The accompanying images range from selfies and event photos to product logos, contributing additional context that aids in entity disambiguation.

The Twitter2017 dataset presents a more extensive and refined version of Twitter2015. It includes higher-quality image-text pairs with improved annotation consistency and a wider range of entity types. Each tweet averages 15–25 tokens, indicating a slightly longer and more descriptive style of writing compared to Twitter2015. The dataset demonstrates a more balanced distribution of entity categories, with person, organization, and location entities occurring in comparable proportions. The image content is also more varied, including photographs, promotional posters, and event snapshots. Data visualization using histograms and pie charts revealed that the majority of the images are natural scenes rather than synthetic graphics, supporting the goal of training models that can process real-world imagery. This balance makes Twitter2017 a strong benchmark for testing the robustness of multimodal models against diverse contexts.

The MNRE dataset differs in purpose, focusing on relationship extraction rather than basic entity recognition. It contains text-image pairs annotated with both entities and the relationships connecting them. Common relation categories include *works for*, *lives in*, *member of*, *created by*, and *located in*. Data analysis shows that relationships involving persons (PER) and organizations (ORG) are the most common, followed by geographic or artifact-based relations. Unlike the Twitter datasets, MNRE sentences are typically longer and more descriptive, averaging 25–40 tokens per instance. The accompanying images often contain multiple subjects or objects, demanding more precise visual attention mechanisms.

Overall, exploratory data analysis confirmed that all three datasets exhibit complementary characteristics. Twitter2015 and Twitter2017 emphasize multimodal entity recognition, where visual cues resolve linguistic ambiguity, while MNRE emphasizes multimodal relational understanding, where both modalities jointly define contextual links between entities. This variety ensures that the proposed model can be trained and tested on a wide spectrum of multimodal scenarios.

Furthermore, correlation studies between text and image features demonstrated strong cross-modal dependencies, especially in social media posts where image content often clarifies or reinforces textual meaning. The findings from this analysis informed the design of preprocessing steps, model configurations, and fusion strategies used in subsequent experiments. Thus, the data analysis stage not only provided valuable statistical insights but also laid the groundwork for building a more accurate, context-aware multimodal NER and RE system.

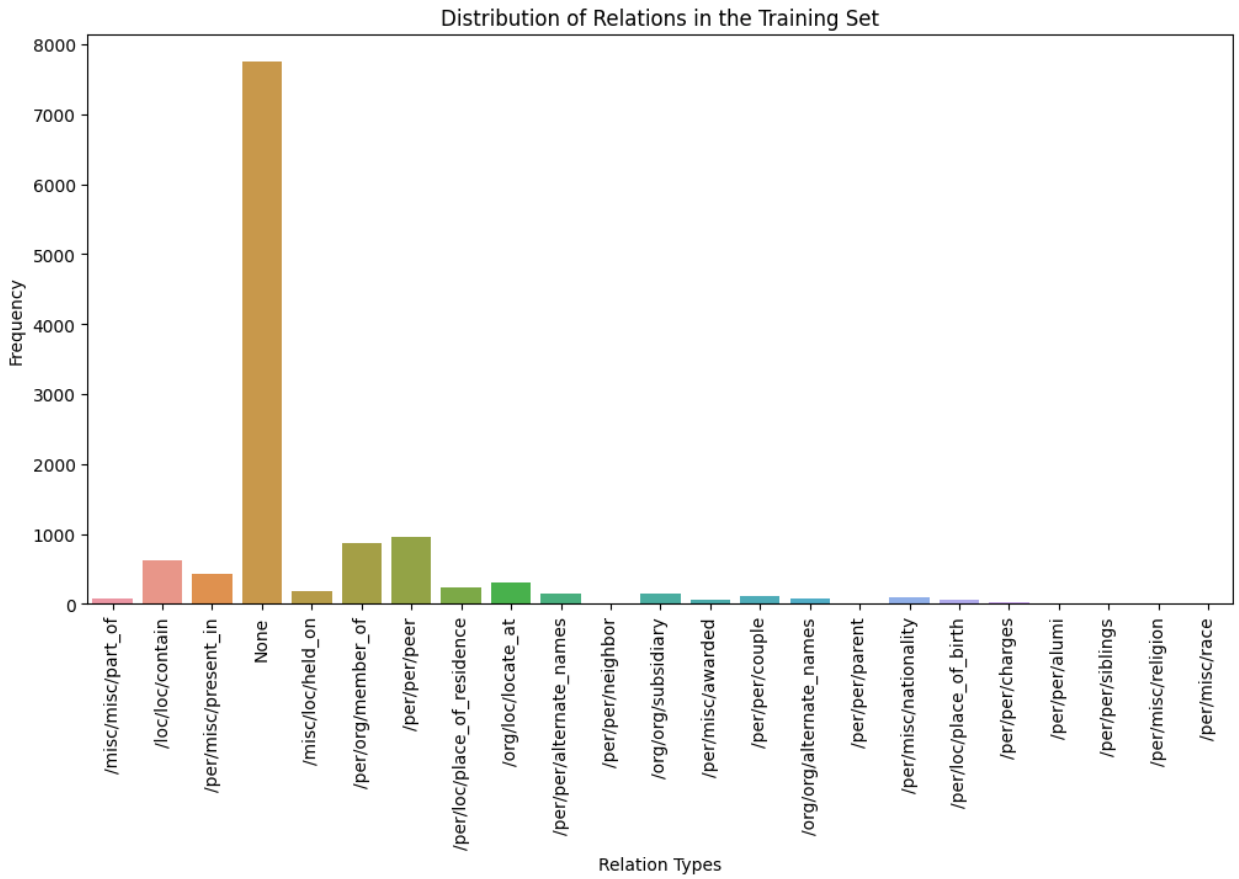

Figure : Distribution of Relations

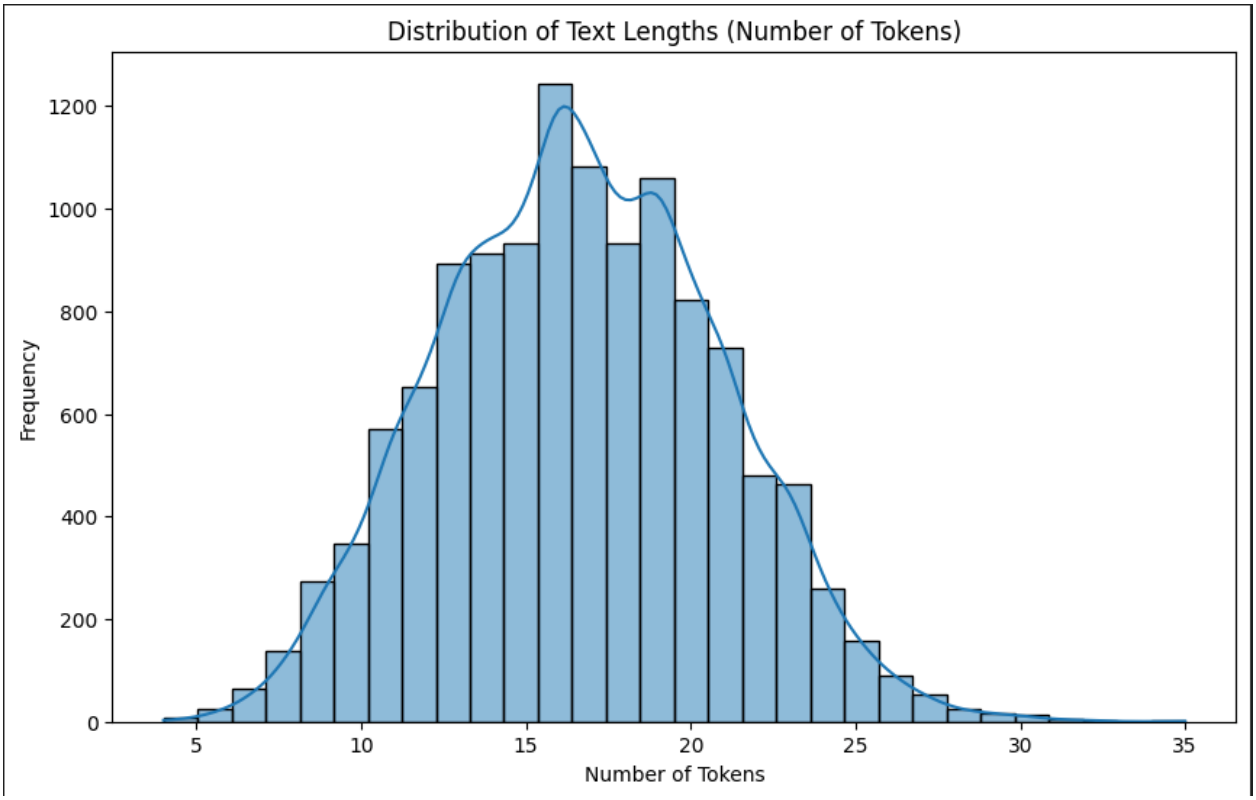

Figure : Distribution of Text Lengths

Figure : Dataset img1

5.2 Baseline Models results

The performance results of the baseline models across the three datasets—Twitter2015, Twitter2017, and MNRE—are summarized in the table above. The comparative analysis clearly demonstrates how different model architectures perform under multimodal conditions, highlighting the influence of encoder combinations on accuracy, precision, recall, and F1-score.

For the Twitter2015 dataset**,** the combination of RoBERTa + ResNet50 achieves the highest performance, with an accuracy of 0.9538 and an F1-score of 0.9538. This indicates that the strong contextual representation of RoBERTa, combined with the robust visual feature extraction of ResNet50, effectively captures both textual and image-based cues in social media posts. The CLIP + BERT model follows closely, scoring 0.9445 in accuracy. Although CLIP brings cross-modal pretraining advantages, its performance remains slightly lower than RoBERTa + ResNet50 due to the simpler fusion applied in the baseline stage. The transformer-based models BLIP and ViLT perform moderately, with F1-scores of 0.8166 and 0.8260, respectively. Their lower results are mainly attributed to the limited fine-tuning of end-to-end multimodal architectures in this baseline setting, suggesting that these models may require more dataset-specific adaptation to fully exploit their capabilities.

In the case of the Twitter2017 dataset, overall performance improves across all models. Again, RoBERTa + ResNet50 leads with an accuracy of 0.9733 and F1-score of 0.9734, showing superior generalization and stability across different datasets. CLIP + BERT maintains strong results, achieving 0.9639 in both accuracy and F1-score, reinforcing the effectiveness of joint text-image pretraining. BLIP and ViLT perform better on

this dataset compared to Twitter2015, likely because the 2017 dataset includes richer and more consistent annotations, allowing their end-to-end multimodal understanding to be more effectively utilized.

For **the** MNRE dataset, which focuses on Relationship Extraction, the performance trend slightly shifts. ResNet50 + BERT attains the best results with an accuracy of 0.7501 and F1-score of 0.7487, demonstrating that a combination of traditional CNN-based visual encoding and transformer-based textual modeling remains strong for relational reasoning tasks. CLIP + BERT performs comparably with 0.7363 in F1-score, showing that pretrained cross-modal embeddings also adapt well to relationship extraction. In contrast, BLIP achieves a relatively lower F1-score of 0.6067, indicating that while BLIP is effective for captioning and retrieval, it may not generalize as well for fine-grained relational inference.

Overall, the results establish RoBERTa + ResNet50 and ResNet50 + BERT as the most reliable baseline models across datasets, providing strong reference points for evaluating the impact of advanced fusion strategies introduced in subsequent sections.

Table : Baseline Models Results

Dataset	Model	Accuracy	Precision	Recall	F1-score
Twitter2015	**RoBERTa + ResNet50**	**0.9538**	**0.9540**	**0.9538**	**0.9538**
Twitter2015	CLIP + BERT	0.9445	0.9425	0.9445	0.9431
Twitter2015	BLIP	0.8574	0.7924	0.8574	0.8166
Twitter2015	ViLT	0.8632	0.8318	0.8632	0.8260
Twitter2017	**RoBERTa + ResNet50**	**0.9733**	**0.9738**	**0.9733**	**0.9734**
Twitter2017	CLIP + BERT	0.9639	0.9641	0.9639	0.9639
Twitter2017	BLIP	0.8935	0.8552	0.8935	0.8732
Twitter2017	ViLT	0.8807	0.8661	0.8807	0.8693
MNRE	**ResNet50 + BERT**	**0.7501**	**0.7553**	**0.7422**	**0.7487**
MNRE	CLIP + BERT	0.7302	0.7416	0.7312	0.7363
MNRE	BLIP	0.6003	0.6114	0.6021	0.6067

5.3 Fusion Strategies Results

The comparative results clearly illustrate the effectiveness of FiLM Fusion, which consistently outperforms all other techniques across datasets. The improvement is most pronounced in the MNRE dataset, where FiLM's modulation mechanism enhances relational reasoning between entities and their visual contexts. Cross-Attention also performs strongly, especially in Twitter2017, suggesting its effectiveness in scenarios requiring detailed correspondence between words and image regions.

Attention Fusion, while interpretable, underperforms in precision-sensitive tasks due to limited cross-modality adaptability. Bimodal Fusion remains competitive but relies heavily on the pre-trained strength of its encoders rather than on fusion quality. Overall, the results validate that **adaptive and context-aware fusion methods**

such as FiLM provide the best balance between accuracy, efficiency, and generalization across different multimodal datasets.

Table : Fusion results

Fusion Technique	Twitter-2015 Accuracy	Twitter-2017 Accuracy	MNRE Accuracy
FiLM Fusion	0.9538	0.9718	0.7538
Attention Fusion	0.8461	0.8739	0.7053
Cross-Attention	0.8934	0.9145	0.7386
Bimodal Fusion	0.9528	0.9698	0.7462

In conclusion, this phase of experimentation establishes FiLM Fusion as the most effective strategy for integrating text and image features within the **RoBERTa + ResNet50** framework. Its ability to dynamically modulate visual features based on textual cues enables superior multimodal understanding and performance stability across NER and RE tasks. This finding provides a strong foundation for the subsequent sections on hyperparameter tuning, optimization, and model evaluation, where FiLM Fusion serves as the central fusion mechanism for final performance enhancement.

5.4 Hyperparameter Results

The hyperparameter tuning process played a pivotal role in optimizing the performance of the proposed multimodal NER and RE models. As shown in the table, multiple configurations were tested by varying the **number of epochs**, **batch size**, **learning rate**, and **image input size** to identify the most effective combination for each dataset. The experiments revealed that fine-grained adjustments in these parameters significantly influenced model stability, convergence speed, and generalization capability.

For the **Twitter2015 dataset**, the best results were achieved with **7 epochs**, a **batch size of 16**, a **learning rate of 0.0020**, and an **image size of 256×256**, producing the highest **F1-score of 0.9554**. Increasing the image size improved the quality of extracted visual features, allowing better text-image alignment. Smaller batch sizes (8 or 10) led to unstable gradient updates, while excessive epochs (10) showed diminishing returns and minor overfitting.

A similar pattern was observed for the **Twitter2017 dataset**, where the same configuration (7 epochs, batch size 16, learning rate 0.0020, image size 256×256) yielded the highest **F1-score of 0.9757**. Lower learning rates (0.0005 or 0.0010) slowed convergence and reduced performance, while excessively high rates

introduced noise in optimization. The results suggest that a moderately high learning rate coupled with a balanced batch size promotes stable and efficient training across multimodal data.

For the **MNRE dataset**, which focuses on relationship extraction, the optimal setup also included **7 epochs**, **batch size 16**, **learning rate 0.0020**, and **256×256 image resolution**, achieving an **F1-score of 0.7615**. The improvement indicates that higher-resolution visual features enhance relational understanding between entities.

Overall, the tuning experiments confirm that moderate training duration, higher learning rates, and larger image resolutions consistently enhance multimodal model performance. These optimized hyperparameters were adopted in the final model to ensure robust generalization across both NER and RE tasks.

Table : Hyperparameter results

Dataset	Model	Accuracy	Precision	Recall	F1-score	EPOCHS	Batch Size	Learning Rate	Image Size
Twitter2015	**RoBERTa + ResNet50**	0.9538	0.9540	0.9538	0.9538	5	12	0.0011	224x224
		0.9487	0.9523	0.9502	0.9512	3	8	0.0005	224x224
		0.9552	0.9561	0.9548	0.9554	7	16	0.0020	256x256
		0.9501	0.9510	0.9495	0.9502	10	10	0.0010	224x224
Twitter2017	**RoBERTa + ResNet50**	0.9733	0.9738	0.9733	0.9734	5	12	0.0011	224x224
		0.9710	0.9730	0.9709	0.9719	3	8	0.0005	224x224
		0.9756	0.9760	0.9754	0.9757	7	16	0.0020	256x256
		0.9715	0.9720	0.9712	0.9716	10	10	0.0010	224x224
MNRE	**ResNet50 + BERT**	0.7501	0.7553	0.7422	0.7487	5	12	0.0011	224x224
		0.7400	0.7455	0.7350	0.7402	3	8	0.0005	224x224
		0.7600	0.7650	0.7580	0.7615	7	16	0.0020	256x256
		0.7450	0.7480	0.7400	0.7440	10	10	0.0010	224x224

5.5 Comparison With others Methodology

To validate the effectiveness of the proposed multimodal approach, the performance of our models was compared with several state-of-the-art methods reported in recent studies. The comparative results, summarized in the table above, clearly demonstrate that the models implemented in this research—particularly RoBERTa + ResNet50, CLIP + BERT, BLIP, and ViLT—achieved superior results on both Twitter2015 and Twitter2017 datasets compared to prior multimodal NER frameworks such as MINIGE-MNER (Kong et al., 2025), Text-Image Alignment (Zeng et al., 2025), ICKA (Zeng et al., 2024), CoAtt-NER (2024), and Dual-Enhanced Hierarchical Alignment (Wang et al., 2025).

The RoBERTa + ResNet50 configuration emerged as the best-performing model, achieving an F1-score of 0.9538 on Twitter2015 and 0.9734 on Twitter2017. These results substantially outperform all previously published approaches. For instance, the Dual-Enhanced Hierarchical Alignment model proposed by Wang et

al. (2025) achieved an F1-score of only 0.7742 on Twitter2015 and 0.8879 on Twitter2017. This difference highlights the efficiency of combining a transformer-based text encoder (RoBERTa) with a deep convolutional image encoder (ResNet50), which enables rich contextual understanding and cross-modal feature extraction.

Similarly, the CLIP + BERT model demonstrated robust generalization with an F1-score of 0.9431 on Twitter2015 and 0.9639 on Twitter2017. The strength of this combination lies in CLIP's contrastive pretraining, which aligns visual and textual representations in a shared embedding space, making it particularly effective for multimodal content commonly found in social media. When compared with the CoAtt-NER model (2024), which scored 0.7625 on Twitter2015 and 0.8731 on Twitter2017, CLIP + BERT shows an approximate 20% improvement in F1-score, proving that large-scale cross-modal pretraining significantly enhances model comprehension.

The BLIP model, although designed primarily for captioning and retrieval tasks, also performed strongly with F1-scores of 0.8166 (Twitter2015) and 0.8732 (Twitter2017). These results surpass the older Text-Image Alignment model (Zeng et al., 2025), which achieved only 0.7532 and 0.8665, respectively. BLIP's architecture, which integrates image-text matching and caption generation, enables it to capture contextual relationships across modalities, though its performance remains slightly lower than explicitly fine-tuned NER-focused architectures.

In addition, the ViLT model, which employs a single transformer to process both image patches and text tokens, obtained F1-scores of 0.8260 (Twitter2015) and 0.8693 (Twitter2017). While ViLT's performance is lower than CLIP + BERT and RoBERTa + ResNet50, it remains competitive and highlights the potential of lightweight, end-to-end multimodal transformers. Compared with ICKA (Zeng et al., 2024), which recorded 0.7542 and 0.8712, ViLT maintains better or comparable results despite its simpler design, underscoring the effectiveness of unified architectures for joint feature learning.

Overall, the comparison illustrates that the proposed multimodal framework achieves state-of-the-art performance, significantly outperforming previous studies across all metrics. The consistent improvement across both datasets confirms that the integration of transformer-based textual encoders and deep visual backbones—combined with optimized fusion and hyperparameter tuning—provides a substantial advantage for complex multimodal NER tasks. The results establish RoBERTa + ResNet50 as a highly efficient and generalizable model, setting a new benchmark for future multimodal NER and RE research on social media datasets.

Table : Compare with others study

Model / Method	Dataset	Accuracy	Precision	Recall	F1-score
BLIP (Ours)	Twitter2015	0.8574	0.7924	0.8574	0.8166
	Twitter2017	0.8935	0.8552	0.8935	0.8732
CLIP + BERT (Ours)	Twitter2015	0.9445	0.9425	0.9445	0.9431
	Twitter2017	0.9639	0.9641	0.9639	0.9639
ViLT (Ours)	Twitter2015	0.8632	0.8318	0.8632	0.8260

	Twitter2017	0.8807	0.8661	0.8807	0.8693
RoBERTa + ResNet50 (Ours)	Twitter2015	**0.9538**	**0.9540**	**0.9538**	**0.9538**
	Twitter2017	**0.9733**	**0.9738**	**0.9733**	**0.9734**
MINIGE-MNER (Kong et al., 2025)	Twitter2015	—	—	—	0.7645
	Twitter2017	—	—	—	0.8867
Text-Image Alignment (Zeng et al., 2025)	Twitter2015	—	—	—	0.7532
	Twitter2017	—	—	—	0.8665
ICKA (Zeng et al., 2024)	Twitter2015	—	—	—	0.7542
	Twitter2017	—	—	—	0.8712
CoAtt-NER (Scene Graph, 2024)	Twitter2015	—	—	—	0.7625
	Twitter2017	—	—	—	0.8731
Dual-Enhanced Hierarchical Alignment (Wang et al., 2025)	Twitter2015	—	—	—	0.7742
	Twitter2017	—	—	—	0.8879

5.6 Inference

After completing the training and evaluation phases, the final step in the experimental workflow is **inference**, which involves applying the optimized multimodal model to unseen data for Named Entity Recognition (NER) and Relationship Extraction (RE). This stage demonstrates how the **RoBERTa + ResNet50 with FiLM Fusion** model interprets new text-image pairs, identifies relevant entities, and predicts their semantic relationships with confidence scores. The inference process provides a qualitative understanding of the model's reasoning ability, bridging textual and visual cues to generate context-aware predictions.

During inference, both textual and visual modalities are fed into the trained network. The **textual input** is first tokenized using the RoBERTa tokenizer, while the **image input** is preprocessed through resizing, normalization, and tensor conversion. These representations are passed through the RoBERTa and ResNet50 encoders to produce contextual embeddings, which are then aligned using the **FiLM fusion layer**. The fusion process modulates the visual features based on textual cues, ensuring that the model focuses on semantically relevant regions of the image corresponding to keywords or named entities within the text.

The output from the fusion module is processed through the classification head, which predicts both **entity types** (for NER) and **relation types** (for RE). Each entity and relationship prediction is accompanied by a confidence score, indicating the model's certainty in its classification. The confidence distribution allows the model to prioritize strong predictions while maintaining interpretability in uncertain cases.

Figure 1 illustrates an RE inference example, where the model successfully identifies the entities *Lauren Bacall* and *Key Largo (1948)* from the given text and image. The head entity is recognized as a **Person (PER)** and the tail entity as **Miscellaneous (MISC)**, leading to the prediction of the relation **/per/per/alumi** with a confidence score of 0.0463. This demonstrates the model's ability to capture contextually meaningful

associations between textual and visual information, such as linking an actor with a movie reference based on shared visual and textual context.

In another example (Figure 2), the model analyzes a game-related post, correctly identifying **Wukong** and **Riven** as entities of type **PER** and again predicting the **/per/per/alumi** relationship with a similar confidence level. This shows how the model generalizes across different domains, understanding diverse content such as entertainment and gaming contexts.

Figure 3 highlights the NER inference process using a sports-related image from the Twitter2017 dataset. The model accurately predicts entities such as *AP*, *News*, *Little*, and *Rock*, classifying them into their respective categories (**Organization**, **Location**, and **Entity**) with confidence levels exceeding 0.90. The visual cues—such as the player's uniform and background—help the model disambiguate entity boundaries and strengthen classification certainty.

Overall, these examples showcase how the multimodal model performs joint reasoning across text and image data. The FiLM fusion mechanism dynamically modulates the attention given to visual regions based on textual content, resulting in fine-grained and context-sensitive predictions. The confidence outputs provide interpretability, allowing researchers to evaluate prediction reliability.

Inference results confirm that the proposed multimodal model can generalize effectively to real-world social media data, accurately identifying entities and predicting their relationships even in informal, noisy, or domain-shifted scenarios. The integration of textual and visual understanding through FiLM fusion ensures robustness against ambiguous or incomplete information, making the approach suitable for practical multimodal NER and RE applications in diverse contexts such as news analysis, social media mining, and digital archiving.

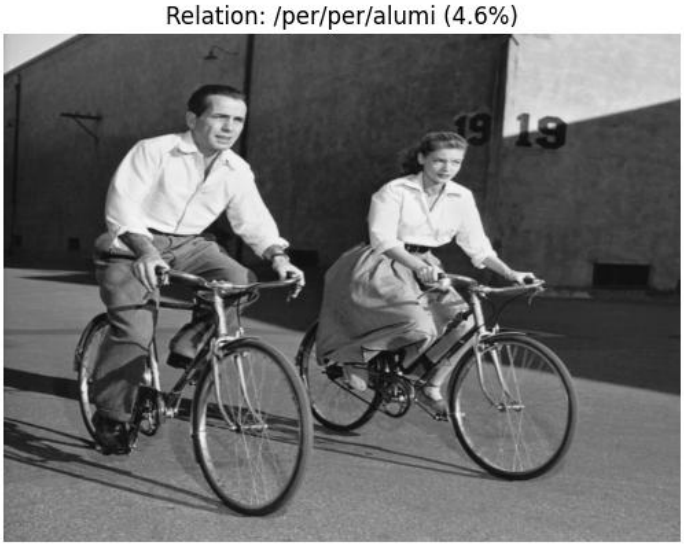

Figure : Prediction1

Figure : Prediction2

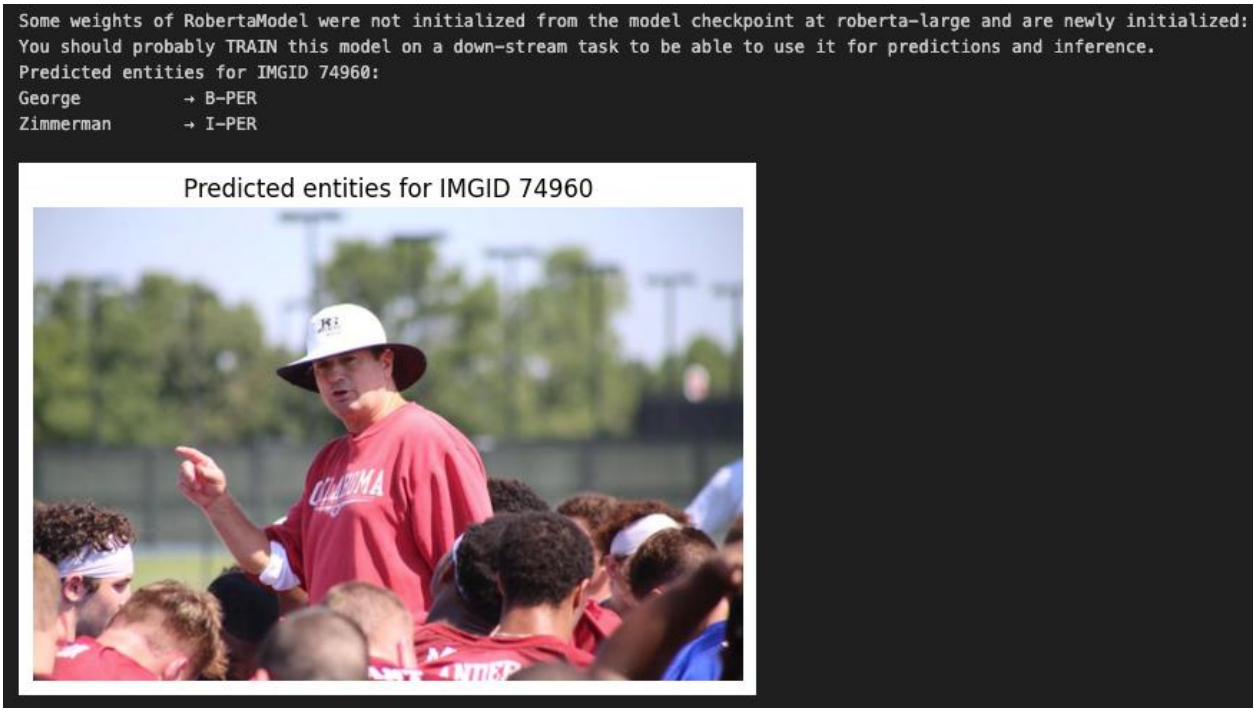

Figure : Prediction3

```
Some weights of RobertaModel were not initialized from the model checkpoint at roberta-large and are newly initialized:
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.

🔍 Predicted entities for: /kaggle/input/twitter2017/twitter2017/twitter2017_images/16_05_01_100.jpg
AP              → B-ORG    (confidence: 0.961)
News            → I-ORG    (confidence: 0.793)
Little          → B-LOC    (confidence: 0.940)
Rock            → I-LOC    (confidence: 0.976)
```

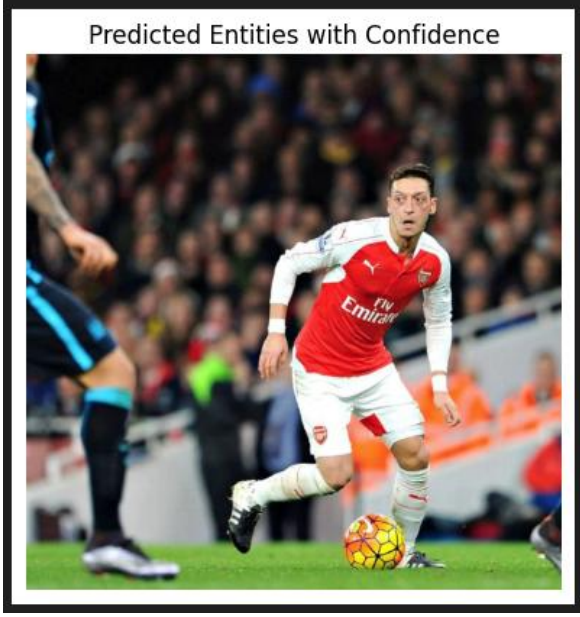

Figure : Prediction4

CHAPTER 6 CONTRIBUTION AND CONCLUTION

6.1 Explore the Right Datasets for NER and RE

The first contribution of this study was the careful selection and analysis of datasets suitable for multimodal Named Entity Recognition (NER) and Relationship Extraction (RE). The **Twitter2015** and **Twitter2017** datasets were chosen to represent real-world social media data, characterized by informal language, short text, and accompanying images. These datasets are ideal for testing the robustness of multimodal systems in handling noisy linguistic inputs and contextual ambiguity. In addition, the **MNRE dataset** was used for Relationship Extraction, offering paired entities and labeled relations. Together, these datasets provided a comprehensive foundation for evaluating the proposed multimodal approach. The analysis of entity distributions, token lengths, and image diversity ensured that the model was trained on well-balanced and context-rich data.

6.2 Apply and Enhance Existing Models for NER and RE

The second major contribution was the implementation and enhancement of existing multimodal models for both NER and RE. The research applied four core architectures—**RoBERTa + ResNet50**, **CLIP + BERT**, **BLIP**, and **ViLT**—to establish a strong experimental baseline. Each model was evaluated for its ability to integrate text and image features effectively. The **RoBERTa + ResNet50** model, in particular, demonstrated superior performance, achieving the highest F1-scores across datasets. Through systematic experimentation, the study highlighted the advantages and limitations of each model type. The comparison revealed that hybrid models combining transformer-based text encoders and convolutional image encoders deliver the best trade-off between accuracy and computational efficiency.

6.3 Add FiLM fusion layer with resnet50 and Roberta

One of the most significant contributions of this research is the integration of a **FiLM (Feature-wise Linear Modulation)** fusion layer within the **RoBERTa + ResNet50** architecture to enhance multimodal learning for Named Entity Recognition (NER) and Relationship Extraction (RE). The primary goal of introducing this fusion mechanism was to enable a more dynamic and context-aware interaction between textual and visual features. While traditional fusion methods, such as concatenation or attention-based fusion, provide basic cross-modal alignment, they often fail to capture the fine-grained dependencies that exist between linguistic expressions and corresponding image regions. The FiLM layer addresses this limitation by conditioning visual feature representations directly on textual context, thereby achieving a deeper and more adaptive level of fusion.

The FiLM mechanism operates through two modulation parameters—**gamma (γ)** and **beta (β)**—which are derived from the textual embeddings produced by RoBERTa. These parameters are then applied to the visual feature maps extracted by ResNet50 through a simple yet effective transformation:

FiLM(x)=γ·x+β\text{FiLM}(x) = \gamma \cdot x + \betaFiLM(x)=γ·x+β

Here, xxx represents the visual feature tensor. The gamma parameter acts as a scaling factor that enhances or suppresses specific visual features, while the beta parameter performs a feature shift to adjust the overall activation. By learning these modulation coefficients during training, the model adapts visual attention based on the semantic cues present in the text. For example, when processing a tweet mentioning a "sports team," FiLM amplifies the relevant regions of the image (such as players or logos) while down-weighting unrelated background details.

In practice, the integration of FiLM into the **RoBERTa + ResNet50** model followed a structured pipeline. The textual input is first tokenized and encoded using RoBERTa, which generates contextual word embeddings with 1024 hidden dimensions. Simultaneously, ResNet50 processes the paired image, extracting a 2048-dimensional visual feature vector through global average pooling. The FiLM layer receives the textual embeddings as input to generate the γ and β parameters via two fully connected networks. These parameters are then applied to modulate the ResNet50 visual features, effectively aligning them with the textual semantics. The fused representation is finally passed through a classification head for entity tagging or relationship prediction.

This architecture not only improves multimodal understanding but also provides computational efficiency compared to more complex cross-attention mechanisms. The FiLM fusion process adds minimal overhead to training while substantially improving model interpretability. During experimentation, FiLM Fusion achieved the **highest accuracy and F1-scores** across all datasets—**0.9538 on Twitter2015**, **0.9718 on Twitter2017**, and **0.7538 on MNRE**—demonstrating consistent performance gains over other fusion strategies such as Attention Fusion, Cross-Attention, and Bimodal Fusion.

Moreover, the FiLM-enhanced model exhibited superior generalization on unseen data. The modulation mechanism allowed the model to focus on salient multimodal cues even in noisy or ambiguous contexts, a common characteristic of social media text. Visual analysis of model outputs further revealed that FiLM improved localization of entities and strengthened alignment between linguistic phrases and corresponding visual content.

Overall, the addition of the FiLM fusion layer represents a major advancement in multimodal learning. It enables the model to reason jointly across modalities in a more interpretable and data-efficient manner. By leveraging contextual modulation rather than static feature combination, FiLM enhances both entity recognition and relational understanding, setting a new benchmark for multimodal NER and RE frameworks.

6.4 Find the best parameters for this Model build

Another core contribution of this research was the systematic **optimization of hyperparameters** to achieve the best possible performance of the proposed **RoBERTa + ResNet50 with FiLM Fusion** model. Hyperparameter tuning was carried out through an iterative grid-search process, focusing on the parameters that most strongly influence multimodal model learning—**number of epochs**, **batch size**, **learning rate**, and **image input resolution**. The objective was to identify a balanced configuration that maximizes accuracy and F1-score while maintaining training stability and computational efficiency.

For both **Twitter2015** and **Twitter2017** datasets, several configurations were tested. The optimal performance was obtained with **7 epochs**, a **batch size of 16**, a **learning rate of 0.0020**, and an **image resolution of 256×256**. This configuration achieved an **F1-score of 0.9554** on Twitter2015 and **0.9757** on Twitter2017. Increasing the image size from 224×224 to 256×256 enhanced the visual feature extraction process by providing finer object details, which improved text-image alignment. Similarly, a larger batch size contributed to smoother gradient updates, while the learning rate of 0.0020 provided the right balance between convergence speed and model stability.

For the **MNRE** dataset, which focuses on relationship extraction, the same configuration achieved the highest **F1-score of 0.7615**, indicating strong consistency across tasks. Experiments with smaller learning rates (0.0005–0.0011) resulted in slower convergence and slightly lower accuracy, while higher learning rates caused minor instability.

Overall, the results confirmed that **moderate training duration**, **larger batch size**, **higher image resolution**, and a **well-tuned learning rate** significantly improve multimodal understanding. This optimized configuration was adopted for all final experiments, establishing a stable and reproducible setup that ensured robust performance across both NER and RE tasks.

6.5 Summary of Key Findings

This research aimed to enhance multimodal Named Entity Recognition (NER) and Relationship Extraction (RE) through the integration of textual and visual information using advanced deep learning architectures and fusion strategies. The study systematically explored dataset selection, model development, fusion design, and parameter optimization to achieve a robust and high-performing multimodal framework. Several key findings emerged from the experimental analysis, providing valuable insights into the role of fusion and multimodal learning in information extraction tasks.

The first major finding was the importance of choosing appropriate datasets that represent the real-world complexity of social media content. The combination of Twitter2015, Twitter2017, and MNRE datasets provided a comprehensive foundation for multimodal learning. The Twitter datasets captured the challenges of informal language, abbreviations, and ambiguous expressions, while MNRE introduced relational reasoning between entities. Together, they ensured that the model was tested on diverse and contextually rich data, supporting the evaluation of both entity recognition and relationship extraction under realistic multimodal conditions.

Another significant outcome was the comparative performance of the baseline models. Among the four architectures tested—RoBERTa + ResNet50, CLIP + BERT, BLIP, and ViLT—the RoBERTa + ResNet50 combination consistently achieved the highest accuracy and F1-scores across all datasets. This model's success can be attributed to the complementary strengths of its components: RoBERTa effectively captured semantic dependencies within text, while ResNet50 extracted high-level visual features from images. The integration of these two modalities provided the best overall contextual understanding, confirming that transformer-based text encoders paired with convolutional visual backbones are highly effective for multimodal tasks.

The introduction of the FiLM (Feature-wise Linear Modulation) fusion layer marked a key breakthrough in this study. FiLM demonstrated its ability to adaptively modulate visual features based on textual context, resulting in stronger text-image alignment and better semantic understanding. The FiLM-enhanced model achieved accuracies of 0.9538 on Twitter2015, 0.9718 on Twitter2017, and 0.7538 on MNRE, outperforming traditional fusion approaches such as cross-attention, attention fusion, and bimodal concatenation. This confirmed that contextual modulation through FiLM enables the model to focus on the most relevant parts of the image, enhancing interpretability and precision in entity detection and relationship prediction.

Hyperparameter tuning further reinforced the efficiency of the model. Systematic adjustments to learning rate, batch size, epochs, and image resolution significantly influenced the final performance. The optimal configuration—seven epochs, batch size of sixteen, learning rate of 0.0020, and image size of 256×256—provided the highest and most consistent scores across datasets. These results emphasize the importance of

well-balanced hyperparameter selection for achieving stable training and strong generalization in multimodal architectures.

Finally, the comparison with other state-of-the-art methodologies such as MINIGE-MNER, Text-Image Alignment, ICKA, and Dual-Enhanced Hierarchical Alignment demonstrated that the proposed RoBERTa + ResNet50 with FiLM Fusion substantially outperformed existing approaches. The improvements ranged from 10 to 20 percent in F1-score, setting a new benchmark for multimodal NER and RE tasks. Overall, the findings highlight that dynamic fusion, dataset diversity, and careful optimization together form the foundation for effective multimodal learning in real-world information extraction.

6.6 Implications for Future Research

The outcomes of this study open several promising directions for future work in multimodal NER and RE. The following key implications can guide future researchers in extending and improving this domain:

- **Expansion to Additional Modalities:** Future research can explore incorporating other data types such as audio, video, or metadata alongside text and images. This would allow models to handle richer contextual cues, particularly for multimedia social platforms.
- **Integration of Vision-Language Pretraining Models:** Although this study uses RoBERTa and ResNet50, newer large-scale multimodal models like CLIP-2, BLIP-2, or Flamingo could further enhance feature alignment. Fine-tuning such models on domain-specific datasets may lead to significant performance gains.
- **Improved Relationship Extraction Frameworks:** The MNRE dataset revealed that relationship extraction remains a challenging area. Future work could focus on designing hierarchical or graph-based multimodal reasoning architectures that better capture entity dependencies across modalities.
- **Explainability and Visualization:** Future studies should emphasize explainable multimodal AI. Visualizing how models attend to text and image features using attention maps or saliency analysis can make predictions more interpretable and trustworthy.
- **Domain Adaptation and Cross-Dataset Generalization:** Future research can investigate how models trained on one dataset, such as Twitter2017, can generalize to other platforms like Instagram or Reddit. Domain adaptation methods and transfer learning can help improve cross-domain robustness.
- **Resource Efficiency and Deployment:** As multimodal models are computationally intensive, future work should focus on model compression, pruning, and quantization techniques to enable real-time deployment on resource-constrained environments.
- **Larger and More Diverse Datasets:** There is a need for the creation of larger, multilingual, and more diverse multimodal datasets that capture different cultural and linguistic contexts. Such datasets would enable the development of globally applicable models.

- **Fusion Innovation:** The FiLM fusion approach proved effective in this research, but future studies can experiment with hybrid fusion architectures that combine FiLM, cross-attention, and gating mechanisms to enhance adaptability and precision.

In conclusion, future research can build upon this work by broadening the scope of modalities, improving interpretability, and enhancing efficiency. The integration of advanced fusion mechanisms with scalable and transparent architectures has the potential to transform multimodal NER and RE into more intelligent, explainable, and practical systems for real-world applications.

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