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Advances in Sentiment Analysis in Deep Learning Models and Techniques

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Abstract- The article investigates the advantages, disadvantages, and areas of research that need more exploration regarding deep learning architectures used in sentiment analysis. These architectures let models learn complex language features from data without explicit feature engineering, changing sentiment analysis. The models' capacity to capture long-range dependencies has improved their context and nuanced expression interpretation, especially in long or metaphorical texts. Deep learning sentiment analysis algorithms have improved, yet they still face obstacles. The complexity of these models raises ethical questions about bias and transparency. They also require huge, annotated datasets and computational resources, which limits their use in resource-constrained contexts. Adopting deep learning models requires balancing performance and practicality. Explore critical deep learning sentiment analysis research gaps. Cross-domain and cross-lingual sentiment analysis requires context- and language-specific models. Textual and non-textual multimodal sentiment analysis offers untapped potential for complex sentiment interpretation. Responsible AI deployment requires model interpretability, robustness against adversarial assaults, and domain consistency. Finally, deep learning and sentiment analysis have changed our knowledge of human emotion. Accuracy and contextual comprehension have improved, but model transparency, data prerequisites, and practical applicability remain issues. Overcoming these restrictions and exploring research gaps will enable responsible sentiment analysis AI innovation.

Keywords- Deep Learning, Natural Language Processing, Sentiment Analysis, Emotion Recognition, Multimodal Sentiment Analysis.

I. INTRODUCTION

Since its inception, sentiment analysis has been an integral part of natural language processing, aiming to uncover the emotional underpinnings of textual content across various domains. Users' increased participation in creating content such as social media posts, product evaluations, and online forums has propelled the demand for automated sentiment analysis techniques that can efficiently categorize opinions and sentiments expressed in text. This demand has driven the exploration and integration of advanced machine learning methodologies. To infer the writers' underlying feelings, attitudes, and subjective judgments, sentiment analysis (also known as opinion mining) categorizes text into positive, negative, or neutral sentiment categories. Conventional sentiment analysis methods often relied on lexicon-based approaches or simple machine learning models that struggled to capture the intricacies of language usage, context, and the ever-evolving nature of linguistic expressions.[1][2] Enter deep learning, a paradigm that harnesses the power of neural networks with multiple layers to model complex relationships within data, allowing for the automatic extraction of features and patterns that were previously challenging to discern. The integration of transfer learning, adversarial training, and reinforcement learning techniques will also be explored to enhance the generalization capabilities of sentiment analysis models across different domains and languages.

As we delve deeper into the intricacies of sentiment analysis through deep learning, we aim to provide readers with a comprehensive overview of the current landscape, methodologies, and challenges in this rapidly evolving field.[3] By understanding the nuances of various deep learning techniques and their applications in sentiment analysis, researchers and practitioners can develop more accurate and effective sentiment analysis models capable of unravelling the complex tapestry of human emotions embedded within textual content. Moreover, this article will shed light on the ethical considerations and potential biases associated with sentiment. analysis models, underscoring the importance of responsible AI deployment and mitigating algorithmic biases in real-world applications. In the subsequent sections, we will explore the key techniques, advancements, and case studies that illuminate the potential and limitations of deep learning in sentiment analysis. Through this exploration, we aim to equip readers with a holistic understanding of the subject and inspire further innovation and research in the pursuit of more accurate, reliable, and ethically sound sentiment analysis solutions.

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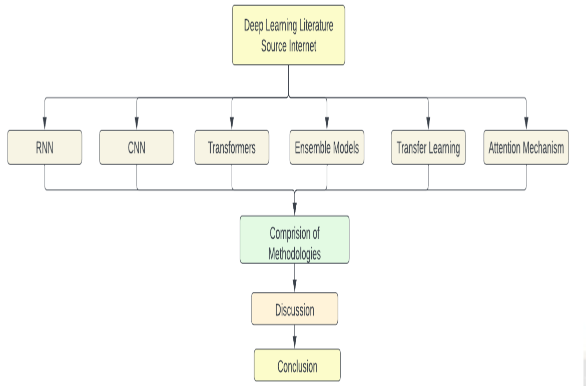

Figure 1: Process flow

II- LITERATURE REVIEW

S. Hochreiter and J. Schmidhuber's (1997) [4]in their proposed study identified that LSTM. effectively tackles the vanishing gradient issue, enabling the capture of long-range dependencies in sequential data. It uses memory cells with gating mechanisms and incorporates word vectors for learning sentiment-relevant embedding. Despite its proficiency in handling sequential data, LSTM's complex architecture demands substantial computational resources and faces challenges with very long sequences. This suggests a need for research exploring variations of LSTM architecture to reduce computational demands and investigating hybrid models combining LSTM with other architectures to enhance sentiment analysis capabilities. Maas et al. (2011) [5] introduced the use of word vectors in "Learning Word Vectors for Sentiment Analysis," significantly enhancing textual data feature representation for improved sentiment analysis. However, the methodology primarily focuses on document-level sentiment analysis, limiting its applicability to fine-grained sentiment tasks.

In Y. Kim's (2014) [6] research, Convolutional Neural Networks were used to achieve exceptional performance in sentence categorization, particularly in challenges at the sentence level. However, it may struggle with capturing long-range dependencies and is limited to fixed-size inputs. Research gaps involve exploring hybrid models combining CNNs with RNNs and techniques for variable-length input processing to broaden its applicability to various text processing tasks and document lengths. Dos Santos and Gatti (2014)[7] presented "Deep Convolutional Neural Networks for Sentiment Analysis of Short Texts," leveraging deep convolutional neural networks for analyzing short textual data. While effective for short texts, it may face challenges with longer documents.

Tang et al. (2015)[8] introduced "Document Modelling with Gated Recurrent Neural Network for Sentiment Classification," which effectively captures sequential information and long-term dependencies. Still, it lacks exploration of attention mechanisms and efficient handling of very large documents. Research should focus on attention mechanisms combined with LSTM for improved sentiment classification and memory-efficient techniques for extensive textual data. Ma and Hovy (2016)[9] integrated end-to-end sequence labelling using CNN.

It offers a comprehensive understanding of text data for sentiment analysis but faces challenges in computational efficiency and architectural configurations. Further research should address these limitations, refine the architecture, and explore various components, including attention mechanisms. Devlin et al. (2018)[10] BERT introduced bidirectional contextual representations, revolutionizing natural language understanding. It excels in various NLP tasks but demands substantial computational resources and may not capture domain-specific nuances effectively. Future research should focus on resource-efficient fine-tuning and domain adaptation methods to optimize BERT for sentiment analysis and specific domains. Radford et al.'s (2019)[11] introduced unsupervised multitask learning for language models. While it excels in various language-related tasks, it may overfit pre-training tasks. Research should explore techniques to prevent overfitting and enhance transferability to sentiment analysis. Vaswani et al. (2017)[12] introduced the Transformer architecture that captures global dependencies with self-attention mechanisms. It excels in various NLP tasks but may face challenges with large-scale tasks and domain-specific or rare words. Research should explore parameter-efficient variants and domain-specific information incorporation. Liu et al.'s (2019)[13] "Roberta" optimized BERT for robust pre-training. It demonstrates versatility in NLP tasks but may not capture sentiment-specific nuances effectively. Research should investigate sentiment-specific pre-training and fine-tuning strategies tailored for sentiment analysis.

Balahur et al. (2019)[14] introduced multimodal sentiment analysis, extending sentiment understanding to text, images, and audio data. This approach enriches sentiment analysis across diverse sources like social media and multimedia content. While advantageous, it entails complexities in integrating multiple modalities and creating labelled datasets. Future research should focus on efficient techniques and scalable methods for managing multimodal data, addressing gaps in this field. Poria et al. (2017)[15] surveyed multimodal sentiment analysis, emphasizing the advantages and drawbacks of this emerging field. It expands sentiment analysis to multiple modalities, enriching context-aware sentiment understanding. However, integrating modalities and creating labelled datasets pose challenges. Future research should explore efficient techniques for handling complexity and scalable methods for large-scale multimodal datasets, advancing this field. Yang et al. (2016)[16] proposed effectively capturing contextual information at different levels. It addresses limitations of traditional methods but may require increased computational resources due to its hierarchical structure. Future research should explore techniques for reducing computational demands and domain-specific adaptations, enhancing document classification. Zhou et al. (2016)[17] introduced Char-CNNs for the classification of text, capturing morphological features. It excels with variable-length text but demands higher computational resources. Research could optimize Char-CNNs for efficiency and assess performance across languages and writing systems. Peng and Dredze (2017)[18] focused on addressing challenges in adapting models to diverse domains. While effective, it involves complexities and demands labelled data for different domains. Future research should refine and automate task selection and adaptation, enhancing multi-domain scenarios.

Li et al. (2016)[19] introduced "Interactive Attention for Sentiment Classification," enhancing sentiment analysis with attention mechanisms. It improves feature selection but adds computational complexity. Research should focus on efficiency and scalability of interactive attention models. Joshi et al. (2017)[20] surveyed "Automatic Sarcasm Detection," offering insights into advancements but lacking extensive performance evaluations. Research should work on standard datasets and cross-lingual detection techniques.

Lan et al.'s (2020)[21] introduction of the ALBERT model offers advantages in efficient self-supervised learning for language representations. Still, challenges include robustness in handling noisy data and scalability for larger lexicons. Sun et al. (2019)[21] focused on low-resource languages in sentiment analysis, using bilingual corpora to adapt models to such languages. Their approach is valuable but may face challenges related to data availability and domain adaptation. Hassan et al. (2022)[23] analysed crypto currency sentiment on Twitter, offering valuable insights, but further research is needed to develop techniques accounting for context-specific sentiment and external factors. Rodrigues et al. (2022)[24] focused on real-time Twitter spam detection and sentiment analysis, using machine learning and deep learning techniques. The paper would benefit from a more extensive discussion of methodologies and the practical challenges of real-time analysis. Alqarni and Rahman (2023)[25] explored sentiment analysis of Arabic tweets during COVID-19 using deep learning. Research gaps include addressing the unique challenges of sentiment analysis in Arabic and examining socio-cultural factors' influence on sentiment. Gupta et al. (2023) proposed a Dengue Disease Prediction and Diagnosis Model, combining sentiment analysis and machine learning. The study should further validate its model's performance in real-world healthcare settings and address potential biases in social media data.

Iqbal et al. (2022)[26] employed deep learning for consumer reviews' sentiment analysis. Future research should explore fine-tuning deep learning models for sentiment analysis in different contexts and languages. Ainapure et al. (2023)[27] conducted sentiment analysis of COVID-19 tweets using deep learning and lexicon-based approaches. To enhance context-specific understanding, the research could explore cultural and regional nuances in sentiment expression. Muhammad and Burney (2023) contributed to Urdu sentiment analysis using various machine and deep learning techniques. The study would benefit from detailed methodology descriptions and a discussion of imbalanced data challenges. Rahman et al. (2023)[28] proposed a multi-tier approach for sentiment analysis in social media text. While the approach is practical, research should address the scalability of supervised machine learning models and their adaptability to evolving language patterns. Additionally, domain-specific nuances in sentiment analysis need consideration.

III-METHODOLOGY

Sentiment analysis, often referred to as opinion mining, is a natural language processing task that involves determining the sentiment or emotional tone expressed in a piece of text, such as a review, comment, or tweet. Deep learning techniques have shown remarkable performance in sentiment analysis due to their ability to automatically learn complex patterns and representations from data. Here are some different methodologies used in sentiment analysis using deep learning.:

1. Recurrent Neural Networks (RNN) are deep learning models for sequential input like text. They understand context and relationships in sentences and documents. Sentiment analysis commonly uses LSTM and GRU Recurrent Neural Networks (RNNs). Traditional RNNs

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are improved to handle long-range dependency by addressing vanishing gradients. Recurrent Neural Networks (RNNs) are good at collecting phrase context and interdependencies since they analyze sequential input. Long-range connections are better captured by LSTM and GRU versions that address vanishing gradients. Recurrent Neural Networks (RNNs) struggle to express long sequences and have large processing costs. They also struggle to accumulate complex language structures. Recurrent Neural Networks (RNNs) evaluate sequences using interconnected units, with LSTM and GRUs being popular. Memory cells and gating mechanisms help these units store contextual data. To handle lengthy sequences more efficiently, research could focus on RNN enhancement. To efficiently capture local and long-range interactions, hybrid models that integrate RNNs with other architectures should be explored.

2. Convolutional Neural Networks (CNNs): The original CNNs were designed for image analysis, however they have been adapted for text sentiment analysis. Convolutional layers capture localized text patterns and attributes for sentence-level sentiment classification. Convolutional Neural Networks (CNNs) may extract important information from text, but they may struggle with distant links. Convolutional neural networks (CNNs) are ideal for sentence-level sentiment classification because they capture subtle local patterns and specific properties in textual input. Their computing efficiency and overfitting resistance are high. CNNs can only analyze a certain size of input and may not capture long-range connections like RNNs. CNNs analyze text and find local patterns using convolutional layers. Deep CNNs can increase feature learning by stacking numerous convolutional layers.

3. Transformers: such as BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer) have demonstrated exceptional performance in several natural language processing (NLP) tasks, including sentiment analysis, and have set new benchmarks in the field.

Transformers, equipped with its self-attention mechanisms, have the ability to extract contextual information from both neighboring and far-reaching words within a sentence. This capability leads to exceptional performance in a wide range of natural language processing tasks, such as sentiment analysis. Transformers necessitate numerous parameters for jobs of significant magnitude and may encounter difficulties with domain-specific or infrequent vocabulary. Transformers utilize self-attention techniques to effectively capture contextual information in textual data. Pre-trained models such as BERT and GPT undergo fine-tuning specifically for sentiment analysis jobs. The research focuses on three primary areas: optimizing transformers to use fewer parameters, integrating domain-specific knowledge into models, and managing the computational requirements of large-scale transformer models.

4. Ensemble Models: Ensemble methods involve combining the predictions of multiple deep learning models to improve accuracy and reduce overfitting. For sentiment analysis, this might involve combining the outputs of an LSTM model, a CNN model, and a BERT model, for example. Ensembles can often yield better results than individual models. Ensemble models combine multiple predictions to enhance accuracy and mitigate overfitting. Ensembles require more computational resources and can be challenging to implement and fine-tune. Multiple deep learning models are used in parallel or sequentially, and their outputs are combined to make final predictions. Research can focus on developing efficient ensemble methods and strategies for combining diverse models effectively.

5. Transfer Learning: Transfer learning techniques involve pre-training models on large text corpora and fine-tuning them on the specific sentiment analysis task. This approach leverages pre-trained language models such as BERT, RoBERTa, or XLNet, saving substantial training time and resources. Fine-tuning is performed on the target sentiment analysis dataset. Transfer learning leverages pre-trained language models, reducing training time and resource requirements. Transfer learning models may require substantial computational resources for fine-tuning and may not effectively capture domain-specific nuances. Pre-trained models like BERT or RoBERT are fine-tuned on a specific sentiment analysis task. Research areas include the development of resource-efficient fine-tuning techniques and strategies for domain adaptation in pre-trained models.

6. Attention Mechanisms: Attention mechanisms, often used in conjunction with RNNs or transformers, allow the model to weigh the importance of different words or sub phrases in a sentence when making predictions. This is particularly useful for identifying the most relevant words or phrases that contribute to sentiment. Attention mechanisms allow models to weigh the importance of words or sub phrases in making predictions, enhancing interpretability. Attention mechanisms may require more computational resources, and their effectiveness depends on model architecture and dataset size. These

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methodologies collectively demonstrate the versatility and power of deep learning in sentiment analysis.

Researchers and practitioners can choose the most suitable approach based on the specific requirements of their sentiment analysis task, the availability of labelled data, and the computational resources at their disposal.

Table 1: Comparison of different methodologies

Model	Advantages	Drawbacks	Applications	Example Literature
Recurrent Neural Network(RNNs)	Captures sequential Dependencies effectively	May struggle with vanishing gradients	Sentence-level sentiment classification.	Hochreiter & Schmidhuber (1997)[4]
	Handles context and long-range Dependencies Suitable for variable length inputs Effective at capturing long range dependencies	Computationally demanding for very long sequences.	Document-level sentiment analysis	Maas et al. (2011)[5]
Convolutional Neural Networks (CNNs)	Efficient at capturing local patterns.	- May not capture long-range dependencies as effectively as RNNs.	- Sentence-level sentiment classification.	Kim (2014)[6]
	- Computationally efficient. Parallelizable architecture.	- Limited to fixed-size input. - May not handle complex sentence structures.	- Aspect-based sentiment analysis.	Zhang et al. (2015)[31]
Transformers	- Captures contextual information efficiently from nearby and distant words. - State-of-the-art performance in NLP tasks.	- May require many parameters for large-scale tasks. - May struggle with domain-specific or rare words.	- Document-level sentiment analysis. - Aspect-based sentiment analysis.	Vaswani et al. (2017)[12] Devlin et al. (2018)[10]
	- Supports parallel processing.	- High computational requirements for training.	- Fine-grained sentiment analysis.	Sun et al. (2019)[22]
Ensemble Models	- Enhanced accuracy through model combination. - Reduces overfitting.	- Increased computational requirements. - Complex to implement and fine-tune.	- Improved generalization. - Handling imbalanced sentiment datasets.	Liu et al. (2013)[43]
Transfer Learning	- Leverages pre-trained models for efficiency.	- Requires substantial computational resources for fine-tuning.	- Rapid model development and deployment.	Howard & Ruder (2018)[32]
	- Effective in resource-constrained settings.	- May not capture domain-specific nuances.	- Few-shot or zero-shot sentiment analysis.	Yang et al. (2019)[16]
Attention Mechanisms	- Enhances interpretability and focus.	- May increase computational resources.	- Aspect-level sentiment analysis.	Wang et al. (2017)[44]
	- Improves model performance with context weighting.		Multilingual sentiment analysis.	
Memory Networks	- Captures sequential information and long-term dependencies.	- May require research into memory-efficient techniques for longer documents.	- Handling longer documents or documents with sequential dependencies.	
	- Supports variable-length inputs.	- May not handle very large documents efficiently.	- Aspect-based sentiment analysis.	Nguyen & Shirai (2017)[47]
Multimodal Approaches	- Captures sentiment across different data types.	- Complex integration of data modalities.	- Social media sentiment analysis with text, images, and audio.	Poria et al. (2017)[15]
	- Holistic understanding of sentiments.	- Increased computational requirements.	- Enhanced context awareness in sentiment analysis.	Balahur et al. (2019)[14]
Hybrid Models	- Combines strengths of different architectures.	- Requires experimentation and parameter tuning.	- Local and long-range sentiment dependencies in text.	Tang et al. (2015)[29]
	- Customizable for specific sentiment analysis needs.		- Multimodal sentiment analysis.	
Self-supervised Learning	- Reduces the need for extensive labeled data.	- Requires careful design for generating high-quality pseudo-labels.	- Efficient use of unlabeled data for sentiment analysis.	Ghosal et al. [51]
	- Resource-efficient training.	- May not fully capture fine-grained sentiment nuances.	- Scalable and cost-effective sentiment analysis.	

IV DISCUSSION

In this review, we have examined a range of methodologies and the corresponding literature used in sentiment analysis, emphasizing the deep learning techniques that have significantly advanced this field. The methodologies discussed encompass a wide spectrum of approaches, each with its own set of advantages, drawbacks, and applications. LSTMs and GRUs, in particular, have been instrumental in mitigating the vanishing gradient problem, making them valuable for long-range dependency modelling. However, they may still pose computational challenges, especially for very long sequences. Convolutional

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Neural Networks (CNNs), initially designed for image analysis, have been adapted for text data with great success. Ensemble models provide a means of combining multiple deep learning models to enhance accuracy and reduce overfitting. However, they require more computational resources and sophisticated implementation. Transfer learning, often using pre-trained models like BERT, offers a valuable shortcut for sentiment analysis tasks by leveraging prior knowledge. While highly effective, it can be computationally intensive for fine-tuning and may struggle to capture domain-specific nuances. Attention mechanisms, memory networks, multimodal approaches, hybrid models, and self-supervised learning each offer unique advantages and applications in sentiment analysis, contributing to the richness of the field's methodologies. Research Gaps :

1. Cross-Domain and Cross-Lingual Analysis : There's a need for research in creating models that can handle sentiment analysis across multiple languages and domains effectively.
2. Multimodal Analysis : Further exploration of advanced multimodal fusion techniques is required, along with handling diverse types of multimodal data sources.
3. Interpretability : Research into improving the interpretability of deep learning models in sentiment analysis is essential for responsible AI deployment.
4. Adversarial Resilience : Developing models that are more robust to adversarial attacks and ensuring model consistency across different domains is an emerging research area.

These findings provide a comprehensive overview of the current landscape, methodologies, advantages, drawbacks, and research gaps in sentiment analysis using deep learning techniques, guiding future research and development in this dynamic field. Techniques such as fine-tuning pre-trained models, adversarial training, and reinforcement learning have improved model generalization across different domains and languages, making sentiment analysis more adaptable.

Deep learning has enabled the integration of text with other data types (multimodal analysis), enhancing sentiment understanding in social media and other platforms where text alone may not convey the full sentiment. The literature emphasizes the importance of ethical considerations and addressing algorithmic biases in sentiment analysis models, highlighting the need for responsible AI deployment.

Sentiment analysis, powered by deep learning methodologies, has made significant strides in understanding, and interpreting human emotions and opinions from textual data. The methodologies discussed in this review provide a diverse toolkit for researchers and practitioners seeking to analyze sentiment in various contexts, from social media sentiment monitoring to customer reviews and beyond. Researchers and practitioners must consider factors such as the availability of labelled data, computational resources, and the nuances of the domain. While each methodology has its own set of advantages and drawbacks, the field continues to evolve, and researchers are actively addressing these limitations. As the demand for sentiment analysis grows, so too does the need for further research into hybrid approaches that can harness the strengths of multiple methodologies and advancements in areas like efficient parameter management, domain-specific adaptation, and the ability to process large-scale datasets. Deep learning methodologies have revolutionized sentiment analysis The ongoing research and development in this field promise further breakthroughs, making sentiment analysis more accurate, efficient, and applicable in an ever-expanding array of real-world scenarios.

V- CONCLUSION

Deep learning algorithms have greatly improved our ability to interpret complicated human emotions in written language. This article examines deep learning architectures and methodologies that have altered sentiment analysis, offering new perspectives for comprehension and analysis. As we conclude our journey, we must consider the main benefits, drawbacks, and research gaps in deep learning-based sentiment analysis. Deep learning in sentiment analysis has enhanced sentiment classification models' precision, adaptability, and resilience. These models may autonomously acquire sophisticated linguistic properties, minimizing the need for manual feature engineering and allowing them to uncover intricate context-dependent word and phrase associations. RNNs and transformers are adept at catching distant associations, which is crucial for interpreting language's subtleties. This capability lets sentiment analysis algorithms detect sentiment changes in long or metaphorical texts.

Pre-trained language models like BERT and its variants have also transformed sentiment analysis. These models, which recognize language patterns and semantics from vast text sets, outperform earlier methods and produce cutting-edge results. Adapting these pre-trained models for sentiment analysis requires a smaller labeled dataset, which reduces data annotation and speeds up sentiment analysis app development in many domains and languages. Deep learning has improved sentiment analysis, yet there are still issues.

The interpretability of these models is crucial. Understanding deep learning architecture predictions becomes harder as they become more complicated.

Lack of transparency makes it difficult to detect and remedy biases or defects in practical implementations, lowering model reliability and raising ethical concerns. Deep learning models need large, annotated datasets to work. Pre-trained models can reduce data shortages, but they may not work in sectors or languages with little training data. This can lead to biased projections and poor performance in resource-constrained situations. In resource-limited environments, deep learning models may require significant computer resources for training and inference, which may restrict their practicality. Deep learning has improved sentiment analysis, however there are still areas that need additional research. One notable field of research is sentiment analysis across domains and languages. Models that adapt to different domains and languages while performing well are the challenge. Multimodal sentiment analysis, which integrates text with visuals and audio, can help understand social media posts and product reviews. The interpretability and explanation of the ability of deep learning models in sentiment analysis constitute another important research avenue. Efforts to enhance the transparency of these models and provide insights into their decision-making processes are crucial to address the ethical concerns associated with AI deployment. Furthermore, the development of robustness-enhancing techniques to mitigate adversarial attacks and ensure model consistency across different datasets and domains is an emerging research frontier. The integration of deep learning in sentiment analysis has propelled the field into new dimensions of accuracy and capability. While the advantages are undeniable, the drawbacks and challenges call for continued research and innovation to foster responsible and ethical AI development. By addressing the existing gaps and leveraging the strengths of deep learning, sentiment analysis can offer richer insights into human emotions, feeling advancements across sectors like marketing, customer service, and public opinion analysis. As researchers and practitioners navigate the dynamic landscape of sentiment analysis, they hold the potential to redefine the way we comprehend and engage with textual sentiments in an increasingly interconnected world.

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