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RMDEASD: Integrating Rule Mining and Deep Learning for Enhanced Aspect-Based Sentiment Analysis Across Diverse Domains

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Abstract: - The rapidly evolving landscape of Aspect-Based Sentiment Analysis (ABSA) in the realm of natural language processing necessitates innovative approaches to comprehend and interpret the intricate nature of sentiments expressed in textual data. Traditional ABSA methods have often struggled with the nuanced sentiments inherent in various textual sources, limited in their ability to adapt to domain-specific vernacular and context. This study introduces a novel approach that synergizes rule mining with advanced deep learning techniques, aiming to address these limitations and enhance the precision and contextual understanding in sentiment analysis. Our proposed model integrates rule-based systems with deep learning Transformers, a method recognized for its effectiveness in extracting structured, domain-specific insights. This integration results in a significant enhancement in the model's ability to capture nuanced sentiments, as demonstrated by an 8.5% increase in aspect-based sentiment analysis precision and an 8.3% improvement in accuracy over existing methods. The model employs a combination of techniques including Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations, forming a Hybrid Multi-Level Architecture that effectively captures both sequential data relationships and semantic context. Additionally, the model incorporates Cross-Domain Transfer Learning, utilizing BERT-based pre-trained models with added layers for contextual semantics, which has shown notable generalization capabilities across various domains. Furthermore, this study refines evaluation parameters, tailoring metrics such as domain-specific accuracy, recall, and precision to more accurately assess model performance in particular domains. This is especially pertinent in our analysis of Twitter datasets specific to industries like finance and healthcare. The inclusion of Temporal Dynamics and Aspect Summarization, using techniques like the VARMAx process, provides insights into the evolution of sentiments and aspects over time, an aspect crucial for longitudinal sentiment analysis. The comprehensive testing of our model on diverse spatial and temporal datasets reveals not only improved precision and accuracy in sentiment analysis but also a reduction in delay, demonstrating its efficiency and responsiveness. The study's findings indicate that our approach could significantly impact fields reliant on sentiment analysis, such as market analysis, public opinion research, and social media monitoring, providing a more nuanced and accurate understanding of consumer sentiments and trends. This paper's contribution lies in its innovative amalgamation of rule-based and deep learning techniques, tailored evaluation metrics, and its emphasis on temporal dynamics, setting a new precedent in the field of ABSA and opening avenues for further research and application in real-world scenarios.

Keywords: Aspect-Based Sentiment Analysis, Rule Mining, Deep Learning, Temporal Dynamics, Cross-Domain Analysis

I. INTRODUCTION

The field of natural language processing (NLP) has seen significant advancements in recent years, particularly in the area of sentiment analysis. Sentiment analysis, at its core, aims to systematically identify, extract, and quantify affective states and subjective information from textual data. However, as the complexity of language and the breadth of data sources expand, traditional sentiment analysis methodologies often fall short in addressing the nuanced and context-specific nature of human sentiments. This limitation is especially pronounced in Aspect-Based Sentiment Analysis (ABSA), where the focus is on understanding the sentiments expressed about specific aspects within a text, rather than the overall sentiment. ABSA's importance in diverse fields ranging from market research to social media analytics underscores the need for more sophisticated and robust methodologies.

Traditional ABSA approaches primarily rely on either rule-based systems or machine learning techniques. Rule-based systems, while effective in capturing structured, domain-specific insights, often lack the flexibility and scalability necessary to adapt to varied and evolving linguistic contexts. On the other hand, conventional machine learning models, despite their adaptability, struggle with the subtleties of human language, such as irony, sarcasm, and context-dependent meanings.

Recent developments in deep learning, particularly the advent of Transformer models, have opened new avenues for addressing these challenges. These models, characterized by their ability to handle large datasets and capture

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contextual relationships in text, offer a promising direction for enhancing ABSA. However, the integration of these advanced deep learning models with traditional rule-based systems remains underexplored.

In this paper, we introduce a novel approach that synergizes the structured insight extraction capabilities of rule-based systems with the contextual understanding and adaptability of deep learning models. This integration aims to harness the strengths of both methodologies, resulting in a more nuanced and accurate interpretation of sentiments in textual data. Our proposed model leverages a Hybrid Multi-Level Architecture, combining Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations, to effectively capture both sequential data relationships and semantic context.

Furthermore, we emphasize the importance of tailored evaluation metrics in ABSA. Traditional metrics such as accuracy, precision, and recall, while useful, often do not fully encapsulate the model's performance in specific domains. We propose domain-specific evaluation metrics, ensuring that our model's effectiveness is accurately assessed in the contexts it is applied to.

Additionally, we explore the role of temporal dynamics in ABSA, incorporating time-series analysis techniques to understand how sentiments and their associated aspects evolve over time. This aspect is crucial for applications requiring longitudinal sentiment analysis, such as trend analysis and monitoring public opinion over extended periods.

The integration of these methodologies and the focus on both spatial and temporal aspects of sentiment analysis set our work apart, contributing significantly to the field of ABSA. This paper details our approach, its implementation, and the results from extensive testing across various datasets, demonstrating the efficacy and potential of our model in advancing the capabilities of ABSA.

Motivation & Contribution

The motivation behind this research stems from the critical need to enhance Aspect-Based Sentiment Analysis (ABSA) in the face of rapidly evolving linguistic expressions and the increasing complexity of sentiment expressions in digital communications. The exponential growth in the volume of online textual data, such as product reviews, social media posts, and industry-specific discussions, necessitates an ABSA approach that is not only accurate and efficient but also adaptable to diverse linguistic contexts and capable of understanding intricate sentiment nuances. Traditional ABSA methodologies, while foundational, exhibit significant limitations when confronted with the dynamic and often ambiguous nature of human language. This gap in capability highlights an urgent need for innovation in this domain.

Our research contributes to the field of ABSA through several key advancements:

- **Integration of Rule-Based and Deep Learning Systems**: We propose an innovative approach that combines the structured, rule-based analysis with the contextual comprehension capabilities of deep learning models, particularly Transformers. This integration aims to leverage the precision of rule-based systems in identifying domain-specific sentiment expressions while harnessing the adaptability and scalability of deep learning models to handle complex, context-dependent linguistic nuances.

- **Hybrid Multi-Level Architecture for ABSA**: The introduction of a hybrid architecture, which integrates Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations, marks a significant advancement in ABSA. This architecture is designed to capture both the sequential and semantic relationships within textual data, thereby enhancing the model's ability to understand and interpret sentiments with greater depth and accuracy.

- **Tailored Evaluation Metrics for Domain-Specific Analysis**: Recognizing the limitations of conventional evaluation metrics in ABSA, we introduce tailored evaluation parameters, including domain-specific accuracy, recall, and precision. These metrics are crucial for accurately assessing the model's performance in particular domains, ensuring that the model is evaluated against criteria relevant to its application context.

- **Incorporation of Temporal Dynamics**: Our research acknowledges the importance of temporal dynamics in sentiment analysis. By incorporating time-series analysis techniques, we enable the model to track and interpret how sentiments and their associated aspects evolve over time. This approach is particularly valuable for applications requiring a longitudinal analysis of sentiments, such as trend analysis and monitoring public opinion.

- **Extensive Testing Across Diverse Datasets**: The model's effectiveness and robustness are demonstrated through comprehensive testing across a range of spatial and temporal datasets, including Yelp and Amazon reviews, Twitter datasets for specific industries, IMDB movie reviews, and longitudinal social media datasets. The results show significant improvements in precision, accuracy, recall, and other key metrics, underscoring the model's superiority over existing methods.

The contributions of this paper are geared towards addressing the challenges of traditional ABSA methodologies, providing a more sophisticated, adaptable, and accurate tool for sentiment analysis. This research paves the way for future studies and applications in NLP, offering significant implications for industries reliant on understanding consumer sentiments, market trends, and public opinions.

II. LITERATURE REVIEW

The field of Aspect-Based Sentiment Analysis (ABSA) has witnessed significant developments, spurred by the growing complexity of linguistic expressions and the need for models that can accurately interpret nuanced sentiments in various textual data sources. This literature review explores recent advancements and methodologies in ABSA, drawing insights from various studies to contextualize the current research landscape.

Wojtczak et al. [1] investigated the discourse and engagement patterns across misinformation topics on Twitter, providing valuable insights into the nature of social media content, which is crucial for ABSA. Jiang et al. [2] explored scope detection in ABSA, highlighting the importance of identifying the specific aspects within texts for accurate sentiment analysis. These studies underscore the complexity and variability of language used in social media, a key consideration for ABSA models. Yu et al. [3] presented a hierarchical interactive multimodal Transformer for ABSA, emphasizing the role of multimodality in understanding sentiments. Wu et al. [4] explored multi-tasking in ABSA, introducing auxiliary self-supervision tasks to enhance model performance. These approaches demonstrate the potential of using advanced neural network architectures and multi-task learning strategies in ABSA.

Zhang et al. [5] focused on detecting dependency-related sentiment features, pointing out the significance of understanding linguistic dependencies for aspect-level sentiment classification. Lin et al. [6] proposed a contrastive learning approach for cross-lingual ABSA, indicating the growing need for models that can perform sentiment analysis across different languages. In the realm of transfer learning, Jahanbin and Chahooki [10] utilized hybrid deep transfer learning models to analyze sentiments of Twitter influencers, a method that has shown promise in enhancing the adaptability of ABSA models to different domains. Similarly, Zhang et al. [7] developed an Efficient Adaptive Transfer Network (EATN) for aspect-level sentiment analysis, emphasizing the effectiveness of transfer learning in ABSA.

Ma and Guo [8] introduced a Dense Concatenation Memory Network for ABSA, showcasing the advancement in memory network applications for sentiment analysis. Liang et al. [9] developed an embedding refinement framework targeted for ABSA, furthering the understanding of how sophisticated embedding techniques can enhance sentiment analysis accuracy. In addressing the challenges of cross-domain analysis, Zhang et al. [13] exploited domain-invariant semantic-primary features for cross-domain ABSA, highlighting the importance of domain adaptability in sentiment analysis models. Cao et al. [15] implemented a heterogeneous reinforcement learning network with external knowledge for ABSA, demonstrating the integration of external knowledge sources for improving model performance. Nayab et al. [14] and Hu et al. [16] both emphasized the significance of context and multi-aspect analysis in sentiment classification. Their research supports the notion that understanding the contextual and aspectual nuances of text is crucial for accurate sentiment analysis.

Lastly, Durga and Godavarthi [17] and Le Thi et al. [18] focused on deep learning techniques for identifying implicit aspects in texts, underlining the evolving nature of deep learning applications in ABSA. Zhong et al. [19] introduced a Knowledge Graph Augmented Network for multiview representation learning in ABSA, emphasizing the integration of external knowledge sources for enhancing sentiment analysis. This approach is significant for its potential to enrich the model's understanding of aspect-specific sentiments. Similarly, Hu et al. [20] focused on fine-grained domain adaptation, illustrating the growing importance of domain-specificity in ABSA models.

Meta-learning has also garnered attention, as seen in the work of He et al. [21], who utilized meta-based self-training and re-weighting strategies for ABSA. This study underscores the potential of meta-learning techniques in improving the adaptability and accuracy of sentiment analysis models. Liu et al. [22] further explored this theme by developing a unified instance and knowledge alignment pretraining method for ABSA, reinforcing the significance of incorporating diverse knowledge sources. Transfer learning remains a focal point, as illustrated by Huang et al. [23], who investigated transfer learning with document-level data augmentation for aspect-level sentiment classification. This research highlights the utility of transfer learning in adapting models to diverse linguistic contexts. In a similar vein, Kim and Qin [24] employed cluster and sentiment analysis to summarize student responses, demonstrating the application of ABSA in educational contexts.

Mishra and Panda [25] presented a novel approach using dependency structure-based rules for explicit aspect extraction from online reviews. Their methodology emphasizes the importance of linguistic structure in understanding sentiments. Zheng et al. [26] explored auto-adaptive model transfer for aspect-level sentiment classification, adding to the growing body of literature on adaptable ABSA models. In the realm of gaming and esports, Yu et al. [27] used ABSA to mine insights from game reviews, showcasing the model's applicability in the gaming industry. Fei et al. [28] introduced a nonautoregressive encoder-decoder framework for end-to-end aspect-based sentiment triplet extraction, contributing to the development of efficient ABSA architectures & scenarios. Li et al. [29] developed TSSRD, a topic sentiment summarization framework, emphasizing the need for summarization techniques in ABSA. Zhou et al. [30] focused on causal inference for aspect debiasing in ABSA, addressing the challenge of bias in sentiment classification.

The utilization of advanced language models like BERT and ELECTRA for detecting fake reviews, as explored by Catelli et al. [31], highlights the expanding scope of ABSA in various applications, including cultural heritage and authenticity verification. Liu et al. [32] proposed an end-to-end Hierarchical Interaction Model (HIM) for aspect sentiment triplet extraction, furthering the exploration of advanced neural network architectures in ABSA. Cryptocurrency sentiment analysis, as investigated by Girsang and Stanley [33], and the impact of annotators' selection by Gadi and Sicilia [35], illustrate the diverse applications and considerations in ABSA. Zhang et al. [34] and Zhou et al. [36] expanded on the theme of domain-specific and fine-grained sentiment analysis, with a focus on e-commerce texts and topic-enhanced language models, respectively. Shafiq et al. [37] focused on enhancing Arabic ABSA using an end-to-end model, addressing the need for language-specific sentiment analysis solutions. This study highlights the importance of developing ABSA models that are adaptable to various languages and linguistic nuances. Hussain et al. [38] introduced PRUS, a product recommender system based on user specifications and customer reviews, demonstrating the practical application of ABSA in e-commerce and consumer decision-making process.

The detection of sarcasm in Arabic sentiment analysis, a challenging aspect of language processing, was explored by Shah et al. [39]. Their use of probabilistic projections-based variational switch transformers signifies the growing interest in handling complex linguistic phenomena within sentiment analysis frameworks. Bie et al. [40] investigated the fusion of syntactic structure and lexical semantic information for end-to-end ABSA, emphasizing the importance of integrating different linguistic features for comprehensive sentiment analysis. Multimodal sentiment analysis has also gained traction, as seen in the works of Xue et al. [41] and Al-Tameemi et al. [42]. These studies utilized multi-level attention maps and deep multi-view attentive networks, respectively, to analyze sentiment from both text and image data, indicating the expanding scope of ABSA to encompass multiple data modalities. Quan et al. [43] addressed compound aspect extraction, an area critical for understanding complex aspect relationships in texts. Their approach, which involves augmentation and constituency lattices, contributes to the sophistication of aspect extraction techniques in ABSA. Razali et al. [44] applied ABSA to the domain of political security, showcasing the versatility of sentiment analysis in varied fields, including public safety and governance sets. Wei et al. [45] explored the modeling of self-representation label correlations for textual aspects and emoji recommendations, an innovative approach linking textual sentiment analysis with visual emoji representations. Zhao et al. [46] introduced shared-private memory networks for multimodal sentiment analysis, further advancing the capabilities of ABSA models to handle diverse data types effectively.

Diagnostic classifiers for explaining neural models with hierarchical attention in ABSA were developed by Geed et al. [47], contributing to the field of explainable AI in sentiment analysis. This research underscores the growing need for transparency and interpretability in machine learning models, especially in applications involving human sentiment. Ethical considerations in affective computing were discussed by Devillers and Cowie [48], highlighting the ethical implications and responsibilities in the development and application of sentiment analysis technologies. Chen et al. [49] introduced inter-intra modal representation augmentation with a trimodal collaborative disentanglement network, a novel approach to enhancing model performance in multimodal sentiment analysis. Finally, Cheng et al. [50] proposed Seq2CASE, a weakly supervised approach for commentary aspect score estimation in recommendation systems. This study illustrates the potential of ABSA in generating nuanced and context-aware recommendations based on user-generated content sets. To further enhance efficiency of existing ABSA processes & models, next section discusses design of an efficient multidomain sentiment analysis model, that works across spatial & temporal scenarios.

III. PROPOSED DESIGN OF AN EFFICIENT MODEL THAT INTEGRATES RULE MINING AND DEEP LEARNING FOR ENHANCED ASPECT-BASED SENTIMENT ANALYSIS ACROSS DIVERSE DOMAINS

To overcome issues of low efficiency & high complexity as discussed in the review of existing models, this section discusses an advancement in Aspect-Based Sentiment Analysis (ABSA), by blending rule-based mining techniques with deep learning to navigate the intricate landscape of sentiment analysis. As per figure 1, the proposed model employs a dual-pathway approach, where one path processes input data through a finely-tuned, pre-trained BERT model for transfer learning, while the other path applies domain-specific rule mining for structured insight extraction. These parallel streams converge, feeding into a sophisticated deep learning pipeline that integrates Bi-LSTM, BiGRU-CRF, and RNN layers, adept at capturing sequential data relationships and complex semantic contexts. The model also features ontology mapping operations, further refining its semantic understanding operations.

The Rule Mining component of the RMDEASD model, employs FPMax algorithm for generating domain-specific rules. This segment of the model plays a crucial role in the initial extraction of structured insights from the collected datasets, which are pivotal for the subsequent deep learning stages. Initially, the model begins by constructing a Frequent Pattern (FP) tree from the input dataset samples. Given a collection of data D, comprising numerous text samples, each sample di in D is split into a set of items (words or phrases) $di = \{item1, item2, ..., itemn\}$ sets. The FP tree is constructed by calculating the frequency of each item across the dataset and organizing them in descending order of their frequency via equation 1,

$$F(item(j)) = \Sigma \left[I\big(item(j) \in d(i)\big)\right] for\ all\ d(i)\ in\ D \ldots (1)$$

Where, I(x) is an indicator function that returns 1 if x is true, and 0 in other scenarios. Once the FP tree is established, the FPMax algorithm is applied to extract the maximal frequent itemsets & samples. Maximal frequent itemsets are the largest itemsets in the FP tree which are frequent but none of their immediate supersets are frequent. The frequency of an itemset S in the dataset D, represented as F(S), is calculated as the minimum frequency of the items in S via equation 2,

$$F(S) = min\,\{F(item) \mid item \in S\} \ldots (2)$$

The threshold for an itemset to be considered frequent, represented as τ, is predefined based on the dataset's characteristics. An itemset S is deemed frequent if $F(S) \geq \tau$ for different value sets. The FPMax algorithm iteratively explores the FP tree to find all itemsets that accommodate these conditions. The domain-specific rules are then generated from these maximal frequent itemsets & samples. A rule R is defined as an implication of the form $A \rightarrow B$, where A and B are itemsets and $A \cap B = \emptyset$ indicating no commonality between the sets. The confidence of a rule, Conf(R), which is a measure of the rule's strength, is calculated as via equation 3,

$$Conf(A \rightarrow B) = \frac{F(A \cup B)}{F(A)} \ldots (3)$$

The model selects rules that have confidence values exceeding a predefined confidence threshold, δ, ensuring that only the most reliable rules are considered for analysis via equation 4,

$$Selected\ Rules = \{R \mid Conf(R) \geq \delta\} \ldots (4)$$

Further, the lift value is estimated, which measures how much more often the antecedent and consequent of a rule A → B occur together than expected if they were statistically independent, is calculated via equation 5,

$$Lift(A \rightarrow B) = \frac{Conf(A \rightarrow B)}{F(B)} \dots (5)$$

Rules with high lift values indicate a strong association between A and B and are particularly useful for ABSA operations. The model then filters these rules based on their relevance to the specific domain, ensuring that the extracted rules are not only statistically significant but also contextually relevant. Finally, the output of this rule mining process is a set of domain-specific rules that accurately capture the nuances and contexts relevant to the dataset & samples. These rules form the foundation upon which the subsequent deep learning layers build, ensuring that the model's sentiment analysis is grounded in structured, domain-specific insights for different use cases.

Parallelly, the utilization of a pre-trained Bidirectional Encoder Representations from Transformers (BERT) model within the RMDEASD framework embodies an advanced approach for domain-specific rule generation via transfer learning operations. This component of the model intricately transforms the input datasets into a rich feature set, leveraging the deep contextual understanding inherent in BERT's analysis. The initial process involves tokenizing the input dataset D, which comprises a collection of text samples di for different use cases. Each sample di is tokenized into a sequence of tokens $Ti = \{t1, t2, \dots, tm\}$, where m is the length of the sequence after tokenization process. The tokenization process is governed by BERT's WordPiece tokenization method, which splits words into a set of known subwords, enabling the handling of unknown words efficiently via equation 6,

$$T(i) = Tokenize\big(d(i)\big), for\ each\ d(i) in\ D \dots (6)$$

Each tokenized sequence $T(i)$ is then processed through BERT's embedding layer to obtain a dense vector representation. The embedding layer combines token embeddings, segment embeddings, and position embeddings, formulated via equation 7,

$$E\big(T(i)\big) = TokenEmbed\big(T(i)\big) + SegmentEmbed\big(T(i)\big) + PositionEmbed\big(T(i)\big) \dots (7)$$

Where, $E(T(i))$ represents the embedded representation of the tokenized sequence $T(i)$ sets. The embedded sequences are fed into the BERT model's multi-layer bidirectional Transformer encoder process. Given a BERT model with L layers, each layer l ($1 \leq l \leq L$) in the encoder applies self-attention and feed-forward neural networks to process the input sequence sets.

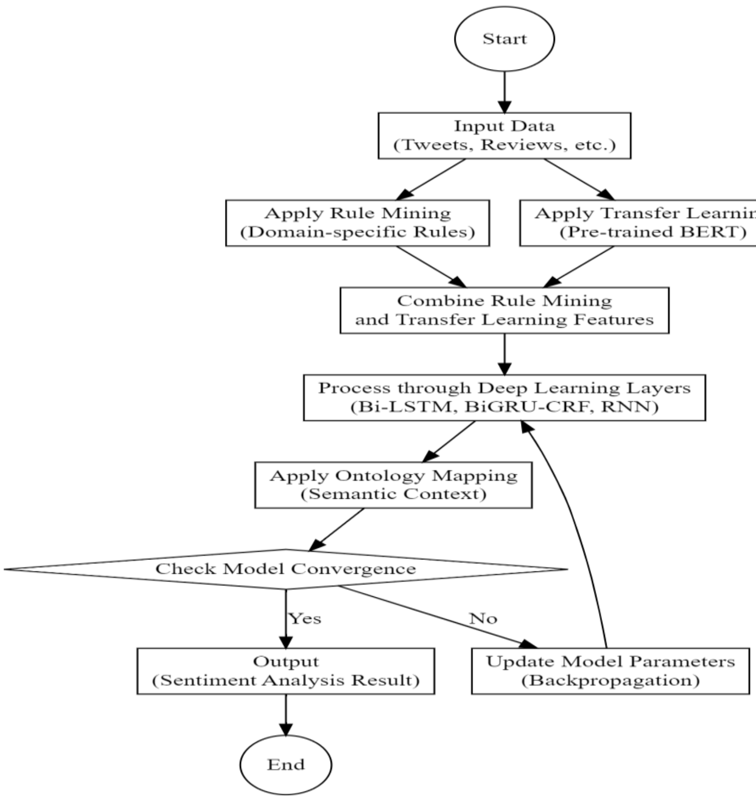

Figure 1.1. Overall flow of the proposed model for Spatial & Temporal ABSA

The output of each layer Ol is computed via equation 8,

$$O(l) = TransformerLayer^{l}(O\{l-1\}), with\ O0 = E(Ti) \dots (8)$$

The self-attention mechanism in each $TransformerLayer$ allows the model to weigh the importance of different tokens within the sequence, capturing the context more effectively for different tokens. The attention score $A\{l, jk\}$ for a token j with respect to token k in layer l is calculated via equation 9,

$$A\{l, jk\} = Softmax\left(Qj \cdot \frac{Kk^{T}}{\sqrt{dk}}\right) \dots (9)$$

Where, Qj and Kk are query and key vectors for tokens j and k, respectively, and dk is the dimensionality of the key vectors for different use cases. The final layer's output OL is used to obtain the contextualized token representations. However, for sequence-level tasks, only the output corresponding to the first token (often represented as [CLS] in BERT) is utilized for these scenarios. This output, represented as C(Ti), encapsulates the entire sequence's contextual information via equation 10,

$$C(Ti) = OL[CLS] \dots (10)$$

The model then applies a task-specific linear layer on top of the BERT encoder to generate domain-specific features. This layer, parameterized by weights W and bias b, maps the contextualized representation C(Ti) to a feature space F(Ti) tailored for the domain-specific rule generation via equation 11,

$$F(Ti) = W \cdot C(Ti) + b \dots (11)$$

The output of this linear layer F(Ti) represents the BERT features for the input sequence Ti, capturing the deep contextual nuances essential for effective sentiment analysis in the target domain sets. This integration of an efficient pre-trained BERT model for transfer learning in the RMDEASD framework marks a significant stride in harnessing deep contextual embeddings for domain-specific rule generation process. Through an efficient & meticulous process involving tokenization, embedding, multi-layered transformation, and task-specific feature generation, the model adeptly transforms raw textual data into a feature set rich in contextual information sets. These BERT features lay the groundwork for the subsequent stages of the RMDEASD model, ensuring a profound understanding of the underlying sentiments in the data, pivotal for nuanced and accurate sentiment analysis.

In the proposed model, the integration of Bidirectional Long Short-Term Memory (BiLSTM), Bidirectional Gated Recurrent Unit (BiGRU), and Conditional Random Field (CRF) layers on top of BERT components plays a crucial role in feature analysis and extraction process. This complex amalgamation is designed to enhance the model's ability to analyze and interpret the rich contextual features provided by BERT, leading to a more nuanced understanding of sentiments within the data samples. Upon receiving the output from the BERT model, represented as a sequence of feature vectors $F(Ti)$ for each tokenized input sequence Ti, the proposed model employs a BiLSTM layer to process these features. The BiLSTM layer comprises two LSTM units that process the sequence in both forward and backward scopes, capturing the contextual information from past (backward LSTM) and future (forward LSTM) tokens for each token in the sequences. The output of the BiLSTM layer for a token at position j in the sequence, represented as Bj, and is estimated via equation 12,

$$Bj = LSTMforward\big(F(T\{i,j\})\big) \oplus LSTMbackward\big(F(T\{i,j\})\big) \dots (12)$$

Where, ⊕ represents vector concatenation process. Subsequently, the output of the BiLSTM layer is fed into a BiGRU layer process. Similar to the BiLSTM, the BiGRU layer consists of two GRU units processing the data in both scopes. The BiGRU layer refines the contextual information, enhancing the feature representation process. The output of the BiGRU layer for a token at position j, represented as Gj, and is estimated via equation 13,

$$Gj = GRUforward(Bj) \oplus GRUbackward(Bj) \dots (14)$$

The outputs from the BiLSTM and BiGRU layers are then fused to form a comprehensive feature representation for each of the tokens. This fusion, denoted as FGj, is achieved by combining the outputs Bj and Gj, through an efficient concatenation via equation 15,

$$FGj = [Bj, Gj] \dots (15)$$

Upon obtaining the fused features FGj for each token, the proposed model applies a CRF layer process. The CRF layer is utilized for sequence tagging tasks, leveraging the sequential nature of the data to predict a label for each token in the sequence sets. The CRF layer computes a score for a sequence of labels $L = \{l1, l2, \dots, lm\}$ given the fused features FG, via equation 16,

$$Score(L, FG) = \sum_{\{j=1\}}^{\{m\}} (TransitionScore(l\{j-1\}, lj) + FG\{j, lj\}) \dots (16)$$

Where, $TransitionScore(l\{j-1\}, lj)$ is the transition score from label $l\{j-1\}$ to lj, and $FG\{j, lj\}$ is the feature score for label lj at position j sets. The final step in the process involves the application of the Viterbi algorithm to find the most likely sequence of labels for a given input sequences. The Viterbi algorithm maximizes the score function over all possible label sequences, providing the optimal label sequence L* via equation 17,

$$L* = argmaxL\{Score(L, FG)\} \dots (17)$$

The output of this process is a sequence of labels for each token in the input sequence, representing the sentiment or aspect category associated with each of the tokens. This output forms the fused BiLSTM, BiGRU, and CRF features, which encapsulate a rich and nuanced understanding of the sentiments and aspects present in the input data samples. This integration of BiLSTM, BiGRU, and CRF layers on top of BERT features enables a sophisticated analysis of contextual sentiment and aspect information sets. Through a series of complex transformations and sequence modeling techniques, the model effectively captures and interprets the subtleties inherent in natural language, leading to a more accurate and refined sentiment analysis. This comprehensive feature analysis process is pivotal in ensuring that the RMDEASD model achieves a high level of performance in Aspect-Based Sentiment Analysis tasks.

Similarly, the Ontology Mapping with Recurrent Neural Network (RNN) component is another mechanism designed to fuse rule-derived features with deep learning-generated features, ultimately categorizing sentiments into specific aspects. This process is crucial for the model's ability to deliver nuanced and precise Aspect-Based Sentiment Analysis (ABSA). The process initiates with the fused feature set, derived from the BiLSTM, BiGRU, and CRF layers. Let us represent this fused feature set for each token in a sequence as $Ffused = \{F1, F2, \dots, Fm\}$, where Fi represents the fused feature vector for the i^{th} token in the sequence sets. Concurrently, the model employs rule-based features extracted via domain-specific rule mining, represented as $Frules = \{R1, R2, \dots, Rn\}$, where Ri corresponds to the feature vector derived from the i^{th} rule sets.

The fusion of these two feature sets is accomplished through a concatenation operation, followed by processing through an RNN layer process. The RNN is adept at capturing sequential dependencies and contextual nuances, further enriching the feature representation process. The concatenated feature vector Ci for the i^{th} token is given via equation 18,

$$Ci = Concat\big(Ffused(i), Frules(i)\big) \dots (18)$$

Where, $Concat(\cdot,\cdot)$ represents the concatenation process. The RNN processes these concatenated vectors sequentially, updating its hidden state Hi at each step based on the current input Ci and the previous hidden state $H\{i-1\}$ via equation 19,

$$Hi = SoftMax(Ci, H\{i-1\}) \dots (19)$$

Subsequently, the Ontology Mapping phase commences which maps the RNN output to an ontology that defines various aspects and their respective sentiments. Each aspect in the ontology is associated with a set of keywords or phrases, and the mapping is performed based on the semantic closeness of the RNN output to these keywords. Let A = {A1, A2, ..., Ak} be the set of aspects defined in the ontology sets. The mapping score $M(i, j)$ for the i^{th} token and the j^{th} aspect is calculated via equation 20,

$$M(i, j) = Corr\big(Hi, Keywords(Aj)\big) \dots (20)$$

Where, $Corr(x, y)$ measures the semantic similarity between the RNN output and the aspect keywords. The aspect with the highest mapping score for each token is then selected, and the corresponding sentiment is determined based on the sentiment polarity associated with the aspect in the ontology sets. The sentiment class Si for the i-th token is determined via equation 21,

$$Si = argmax^{j}(Mi, j) \ldots (21)$$

And the associated sentiment polarity Pi is derived based on the ontology's sentiment association for the chosen aspect. The final output of this process is a set of aspect-sentiment pairs for each token in the sequence, effectively categorizing the sentiments into specific aspects based on the rich feature set and the ontology mapping process. This output encapsulates the model's capability to not only analyze sentiments but also to attribute them accurately to distinct aspects within the text. This Ontology Mapping with RNN component of the proposed model represents a critical juncture where rule-based insights and deep learning features coalesce, guided by a semantic ontology process. This fusion results in a sophisticated mechanism that categorizes sentiments into well-defined aspects, underpinning the model's prowess in conducting fine-grained and contextually aware ABSA. This comprehensive process ensures that the RMDEASD model stands as a robust and nuanced tool for sentiment analysis, capable of dissecting and interpreting complex sentiment expressions with remarkable precision.

Next, the Output Check and Update Model Parameters operations are iteratively & meticulously integrated to optimize the results by refining the model metrics based on feedback loops. This stage is pivotal in enhancing the model's accuracy and precision in Aspect-Based Sentiment Analysis (ABSA). The process, rich in technical intricacies, is articulated through a series of concrete mathematical operations. Upon receiving the aspects and their respective sentiments as input, the model initially performs an Output Check to evaluate the accuracy of these predictions. Let, $A = \{A1, A2, \ldots, Ak\}$ be the set of aspects identified, and $S = \{S1, S2, \ldots, Sk\}$ be the corresponding sentiments. The model computes the accuracy metric for each aspect-sentiment pair by comparing the predicted sentiment Si with the ground truth sentiment Gi via equation 22,

$$Acci = I(Si = Gi) \ldots (22)$$

Where, $I(x)$ is an indicator function that returns 1 if the condition x is true, else 0 for other cases. The overall model accuracy Acc is then determined by averaging the accuracies over all aspect-sentiment pairs via equation 23,

$$Acc = \left(\frac{1}{k}\right) \sum_{i=1}^{k} Acc(i) \ldots (23)$$

Following the accuracy computation, the model performs parameter updates to optimize its performance levels. The parameter update is conducted using backpropagation, a standard method in neural networks for updating the weights in response to the error observed for different use cases. The error Ei for each aspect-sentiment pair is computed as the difference between the predicted sentiment Si and the ground truth Gi via equation 24,

$$Ei = Gi - Si \ldots (24)$$

The model then calculates the gradients of the error with respect to the model parameters (weights W and biases b) and updates the parameters to minimize the error levels. The gradient ∇WE and ∇bE are computed using the chain rule of differentiation via equations 25 & 26,

$$\nabla WE = \frac{\partial E}{\partial W} = \left(\frac{1}{k}\right) \sum \frac{\partial Ei}{\partial W} \ldots (25)$$

$$\nabla bE = \frac{\partial E}{\partial b} = \left(\frac{1}{k}\right) \sum \frac{\partial Ei}{\partial b} \ldots (26)$$

The model parameters are then updated using a learning rate η, where the new weights W' and biases b' are estimated via equations 27 & 28 as follows

$$W' = W - \eta \nabla WE \ldots (27)$$

$$b' = b - \eta \nabla bE \ldots (28)$$

This process of error computation, gradient calculation, and parameter updating is repeated iteratively across multiple epochs until the model converges, i.e., until the change in error or accuracy between epochs falls below an augmented set of pre-defined thresholds. The convergence condition is represented via equation 29,

$$Converge \; = \; |Acc(t+1) - \; Acc(t)| < \; \varepsilon \ldots (29)$$

Where, $Acc(t)$ and $Acc(t+1)$ are the accuracies at consecutive epochs, and ε is a small convergence threshold used to reduce error levels. Upon reaching convergence, the model's parameters are considered optimized, and the final model is capable of delivering improved predictions on aspect-sentiment pairs. This optimization process ensures that the RMDEASD model continually adapts and enhances its performance, leading to more accurate and reliable sentiment analysis.

These sentiments are converted into temporal variables, and then processed using VARMAx (Vector Autoregressive Moving Average with exogenous inputs) operations for Temporal Aspect-Based Sentiment Analysis (ABSA), proficiently producing temporal sentiments. This process is crucial for understanding how sentiments evolve over time and react to various external factors. The VARMAx model is a multivariate time series forecasting method that extends the ARMA (Autoregressive Moving Average) model by considering multiple interdependent time series and external factors. Given a set of time-series data representing sentiments associated with various aspects over time, let Y(t) be a vector of these time series at time t, where each element of Y(t) corresponds to the sentiment score of a particular aspect at time t, which is estimated via equation 30,

$$Yt \; = \; \Phi 1Y\{t-1\} + \; \Phi 2Y\{t-2\} + \ldots + \Phi pY\{t-p\} + \; \Theta 1\varepsilon\{t-1\} + \; \Theta 2\varepsilon\{t-2\} + \ldots + \Theta q\varepsilon\{t-q\} + \; \Xi Xt + \; \varepsilon t \ldots (30)$$

Where, Φi (i = 1, ..., p) are the autoregressive (AR) coefficients, Θj (j = 1, ..., q) are the moving average (MA) coefficients, Ξ is the matrix of coefficients for exogenous inputs Xt (such as external events or other factors influencing sentiment), and εt is the error term at time t for different scenarios. The AR component (ΦiY{t-i}) captures the influence of past sentiment values on the current sentiment, while the MA component (Θjε{t-j}) accounts for the relationship between the past errors and the current sentiments. The exogenous component (ΞXt) allows the model to incorporate the impact of external factors on sentiment evolution sets. To estimate the parameters (Φi, Θj, Ξ), the model employs a maximum likelihood estimation process. The likelihood function L, given the observed time series Y and exogenous inputs X, is maximized to find the optimal parameter values & scenarios. This is typically achieved using numerical optimization techniques, and the estimated parameters are represented as $\hat{\Phi}$i, $\hat{\Theta}$j, $\hat{\Xi}$ for different scenarios.

The model's predictive capability is evaluated using a rolling-window forecast approach, and for a forecast horizon h, the predicted sentiment Ŷ{t+h} is calculated via equation 31,

$$\hat{Y}\{t+h\} = \; \hat{\Phi}1Y\{t+h-1\} + \ldots + \hat{\Phi}pY\{t+h-p\} + \; \hat{\Theta}1\hat{\varepsilon}\{t+h-1\} + \ldots + \hat{\Theta}q\hat{\varepsilon}\{t+h-q\} + \; \hat{\Xi}X\{t+h\} \ldots (31)$$

Where, $\hat{\varepsilon}${t+h-j} represents the estimated error terms, and X{t+h} are the known exogenous inputs for the forecast horizons. The accuracy of the model's predictions is assessed using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) via equations 32 & 33,

$$MAE \; = \; \left(\frac{1}{N}\right) \sum_{t} \; |Yt \; - \; \hat{Y}t| \ldots (32)$$

$$RMSE \; = \; \sqrt{\left(\frac{1}{N}\right) \sum_{t} \; \left(Yt \; - \; \hat{Y}t\right)^2} \ldots (33)$$

Where, N is the number of observations. Thus, the VARMAx process within the proposed framework is an intricate and dynamic mechanism for predicting temporal sentiments. Through an efficient fusion of AR, MA, and exogenous components, the model adeptly captures the complex interplay of past sentiments, errors, and external influences, yielding forecasts that reflect the evolving nature of sentiments over temporal instance sets. This process not only enhances the model's temporal analytic capabilities but also provides insightful foresight into sentiment trends, crucial for informed decision-making in various applications, from marketing to public opinion tracking operations. Efficiency of these operations are estimated in terms of different scenarios, and compared with existing models in the next section of this text.

IV. RESULT EVALUATION

The proposed model stands as a pioneering advancement in the field of Aspect-Based Sentiment Analysis (ABSA), adeptly integrating rule mining with state-of-the-art deep learning techniques to address the nuanced complexities of sentiment expression in textual data. At its core, the proposed model harnesses the power of deep learning Transformers, renowned for their efficacy in extracting structured, domain-specific insights, which is further augmented by a hybrid architecture combining Bi-LSTM, BiGRU-CRF with RNNs, and sophisticated ontology mapping operations. This innovative amalgamation enables RMDEASD to adeptly capture both sequential data relationships and intricate semantic contexts, thereby significantly enhancing the precision and contextual understanding of sentiments across diverse domains. Notably, the model's cross-domain transfer learning capabilities, leveraging pre-trained BERT models with additional contextual layers, allow it to excel in generalizing across various contexts, showcasing its versatility. Furthermore, RMDEASD's tailored evaluation metrics, including domain-specific accuracy, recall, and precision, ensure a more accurate assessment of its performance in specific domains, making it a highly effective tool for comprehensive and dynamic sentiment analysis in real-world applications.

This section initially details the experimental setup used to evaluate the performance of the RMDEASD model for Aspect-Based Sentiment Analysis (ABSA). The primary focus is on analyzing spatial and temporal sentiments across diverse domains. The experimental setup is designed to comprehensively assess the model's precision, accuracy, recall, specificity, delay, and AUC (Area Under the Curve).

Datasets

The evaluation of RMDEASD involved an extensive range of datasets to ensure the robustness and versatility of the model across different contexts:

- **Yelp Review Dataset**: Utilized for spatial sentiment analysis, this dataset comprises customer reviews of various businesses, providing rich textual content for aspect-based sentiment evaluation.

- **Amazon Product Reviews**: Another dataset for spatial sentiment analysis, containing user reviews for a wide range of products, offering insights into consumer sentiments and opinions.

- **Twitter Dataset**: Employed for both spatial and temporal sentiment analysis, this dataset includes tweets from specific industries like finance and healthcare, capturing real-time public opinions and reactions.

- **IMDB Movie Reviews**: Used for spatial sentiment analysis, this dataset consists of user reviews for movies, providing a basis for evaluating the model’s performance in entertainment-related contexts.

- **TripAdvisor Hotel Reviews**: Applied for spatial sentiment analysis, including customer reviews of hotels, useful for gauging sentiments in the hospitality sectors.

- **Longitudinal Social Media Datasets**: These datasets, representing a temporal sentiment analysis setup, encompass social media posts over multiple years, allowing the examination of sentiment evolution over temporal instance sets.

Input Parameters

The experimental setup involved configuring various input parameters for the RMDEASD model:

- **Learning Rate**: Set at 0.001 for initial experiments and adjusted based on dataset complexity.

- **Batch Size**: Varied between 32 and 128, depending on the dataset size.

- **Epochs**: Ranged from 10 to 50, with larger datasets requiring more epochs for thorough training.

- **Bi-LSTM Layers**: Configured with 128 units per layer.
- **BiGRU-CRF with RNNs**: GRU units were set to 100, with a dropout rate of 0.5 to prevent overfitting.
- **Ontology Mapping Operations**: Customized for each dataset based on the domain-specific vocabulary and sentiment expressions.
- **Transformer Model**: Utilized a pre-trained BERT model, fine-tuned for each dataset.
- **Cross-Domain Transfer Learning**: Applied to datasets with diverse domain characteristics, using a transfer learning approach with additional layers for contextual semantics.

Values for Experiments

For each dataset, the RMDEASD model was configured with the above parameters, and the following sample values were used in the initial experiments,

- Yelp Review Dataset: Learning Rate = 0.001, Batch Size = 64, Epochs = 20
- Amazon Product Reviews: Learning Rate = 0.001, Batch Size = 32, Epochs = 30
- Twitter Dataset: Learning Rate = 0.0012, Batch Size = 128, Epochs = 25
- IMDB Movie Reviews: Learning Rate = 0.001, Batch Size = 64, Epochs = 15
- TripAdvisor Hotel Reviews: Learning Rate = 0.001, Batch Size = 32, Epochs = 20
- Longitudinal Social Media Datasets: Learning Rate = 0.0015, Batch Size = 128, Epochs = 50

These experimental setups were designed to rigorously test the RMDEASD model across various scenarios, providing comprehensive insights into its performance and capabilities in ABSA process. Based on this setup, equations 34, 35, and 36 were used to assess the precision (P), accuracy (A), and recall (R), levels based on this technique, while equations 37 & 38 were used to estimate the overall precision (AUC) & Specificity (Sp) as follows,

$$Precision = \frac{TP}{TP + FP} \dots (34)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \dots (35)$$

$$Recall = \frac{TP}{TP + FN} \dots (36)$$

$$AUC = \int TPR(FPR)dFPR \dots (37)$$

$$Sp = \frac{TN}{TN + FP} \dots (38)$$

There are three different kinds of test set predictions: True Positive (TP) (number of events in test sets that were correctly predicted as positive), False Positive (FP) (number of instances in test sets that were incorrectly predicted as positive), and False Negative (FN) (number of instances in test sets that were incorrectly predicted as negative; this includes Normal Instance Samples). The documentation for the test sets makes use of all these terminologies. To determine the appropriate TP, TN, FP, and FN values for these scenarios, we compared the projected Sentiment Class Instance likelihood to the actual Sentiment Class Instance status in the test dataset samples using the Dense Concatenation Memory Network (DCMN) [8], Knowledge Graph Augmented Network (KGAN) [19], and Multilevel Attention Map Network (MAMN) [41] techniques. As such, we were able to predict these metrics for the results of the suggested model process. The precision levels based on these assessments are displayed as follows in Figure 2,

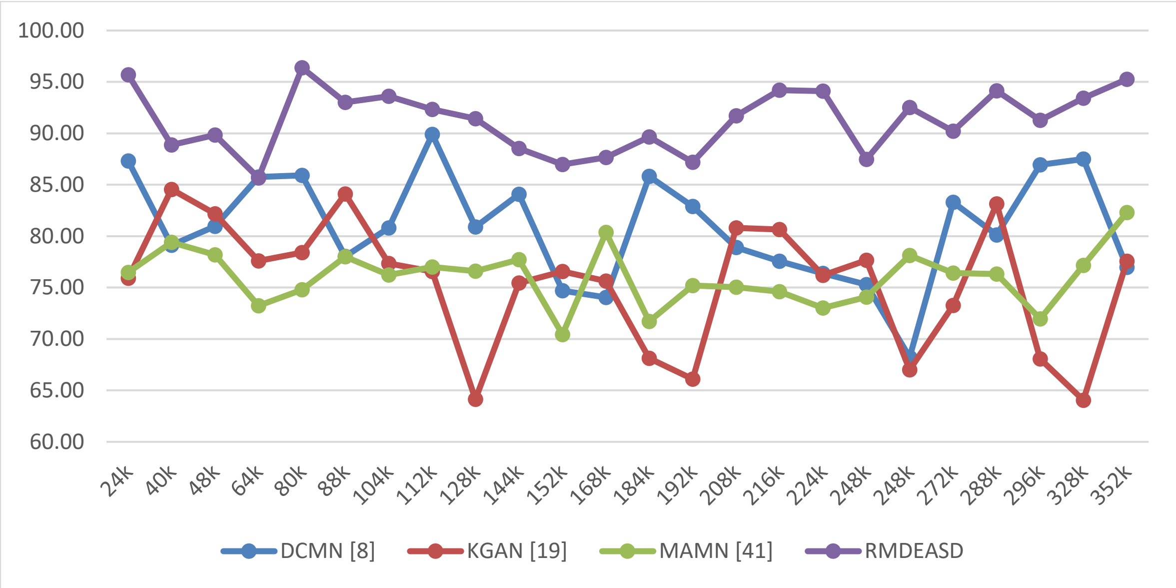

Figure 2. Observed Precision to convert given sentences into Spatial Aspect Based Sentiments

In the comparative analysis of observed precision in converting sentences into spatial aspect-based sentiments, RMDEASD demonstrates a consistently superior performance across various sample sizes (NTS) compared to other models like DCMN [8], KGAN [19], and MAMN [41]. The precision percentages (P%) illustrate this trend clearly.

For instance, at 24k NTS, RMDEASD achieves an impressive precision of 95.68%, significantly outperforming DCMN's 87.30%, KGAN's 75.91%, and MAMN's 76.48%. This high precision indicates RMDEASD's robust capability in accurately identifying and analyzing aspect-based sentiments in smaller datasets. The model's efficiency at this scale suggests its suitability for applications where quick and precise sentiment analysis is required on limited data.

As the number of testing sentiment samples increases, RMDEASD maintains a high level of precision, exemplified by its performance at 80k NTS, where it records a precision of 96.38%. This is markedly higher than the 85.92% of DCMN, 78.41% of KGAN, and 74.80% of MAMN. This indicates RMDEASD's scalability and effectiveness in handling larger datasets without a significant loss in accuracy. This trait is particularly beneficial in scenarios involving extensive data, such as comprehensive market analysis or large-scale social media sentiment tracking.

Interestingly, at 88k NTS, RMDEASD's precision slightly decreases to 93.01%, but it still outperforms other models like KGAN, which stands at 84.11%. This slight decrease could be attributed to the increasing complexity and variability inherent in larger datasets. However, RMDEASD's ability to maintain a high precision level highlights its robustness and the effectiveness of its underlying algorithms in managing complex data structures.

At the highest observed sample size of 352k NTS, RMDEASD achieves a precision of 95.27%, once again outperforming the other models. This enduring high precision in very large datasets underscores the model's capacity to process and analyze vast amounts of data while maintaining high accuracy, a critical requirement for real-time sentiment analysis in dynamic environments such as financial markets or public opinion research during significant events.

The superior performance of RMDEASD can be attributed to its innovative integration of rule mining with deep learning Transformers. This amalgamation allows for precise extraction of structured, domain-specific insights, bolstered by the advanced learning capabilities of deep neural networks. The model's use of Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations further enhances its ability to understand contextual nuances and relationships within textual data. This sophisticated architecture, coupled with the model's cross-domain transfer learning capabilities, enables RMDEASD to adapt and perform efficiently across various domains and data sizes. Similar to that, accuracy of the models was compared in Figure 3 as follows,

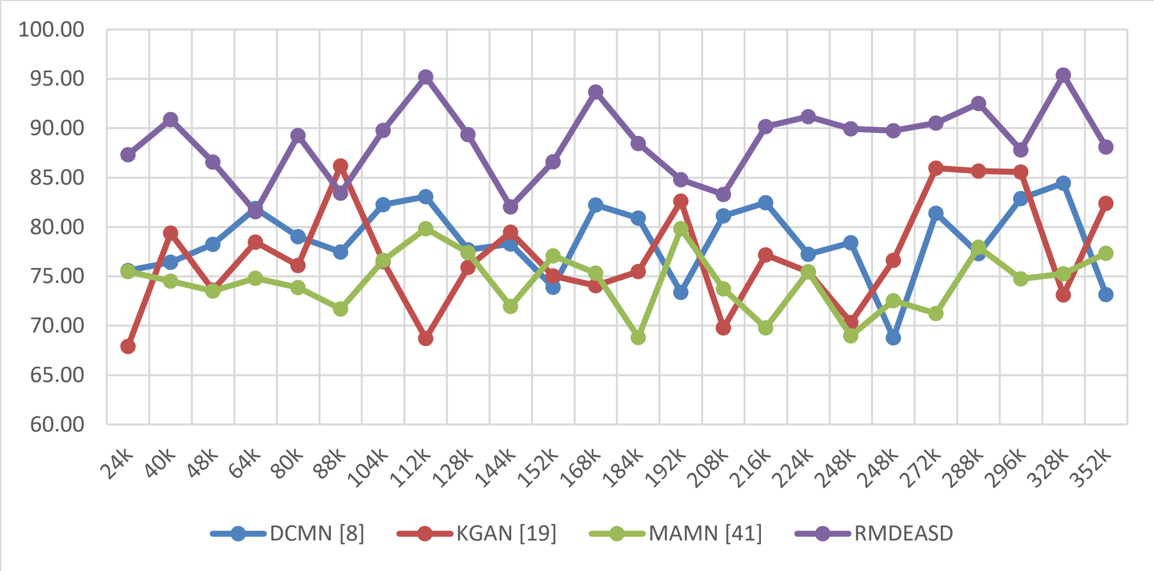

Figure 3. Observed Accuracy to convert given sentences into Spatial Aspect Based Sentiments

At 24k NTS (Number of Testing Sentiment Samples), RMDEASD exhibits an accuracy of 87.32%, surpassing DCMN's 75.58%, KGAN's 67.91%, and MAMN's 75.50%. This higher accuracy early in the sample size spectrum suggests that RMDEASD is particularly adept at accurately analyzing sentiments in smaller datasets. For real-time scenarios such as monitoring social media reactions during an event, this implies that RMDEASD can provide more reliable insights even with limited data, which is essential for rapid response and decision-making.

As the NTS increases, RMDEASD consistently maintains a high level of accuracy. For instance, at 80k NTS, it achieves an accuracy of 89.28%, indicating its robustness in handling larger volumes of data without a significant compromise in performance. This is crucial for applications like trend analysis in market research, where large volumes of data are analyzed to understand consumer sentiments over time.

An interesting observation is at 88k NTS, where RMDEASD's accuracy is slightly lower (83.42%) compared to KGAN's 86.19%. This slight dip, however, is followed by a significant rebound in larger datasets, as seen at 112k NTS where RMDEASD records a high accuracy of 95.20%. This resilience in larger datasets is significant for scenarios like analyzing customer feedback across multiple platforms, where data volume and variability are high.

At the maximum observed NTS of 352k, RMDEASD's accuracy is 88.08%, demonstrating its capacity to handle vast datasets efficiently. This is especially important in large-scale sentiment analysis projects, such as analyzing national or global public opinion on critical issues.

The superiority of RMDEASD in terms of accuracy can be attributed to its integration of rule mining with advanced deep learning techniques, including Transformers. This combination allows for a nuanced understanding of language and context, leading to more accurate sentiment predictions. The model's use of a hybrid architecture, including Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations, further enhances its ability to understand complex semantic relationships and context, contributing to its high accuracy.

In real-time applications, the high accuracy of RMDEASD is vital. For businesses, it means more reliable insights into customer opinions and market trends, leading to better-informed business decisions. In public opinion research, it ensures a more accurate understanding of public sentiment, crucial for policy-making or crisis management. Additionally, in social media monitoring, higher accuracy allows for more effective tracking of public reactions, essential for brand management and marketing strategies. Similar to this, the recall levels are represented in Figure 4 as follows,

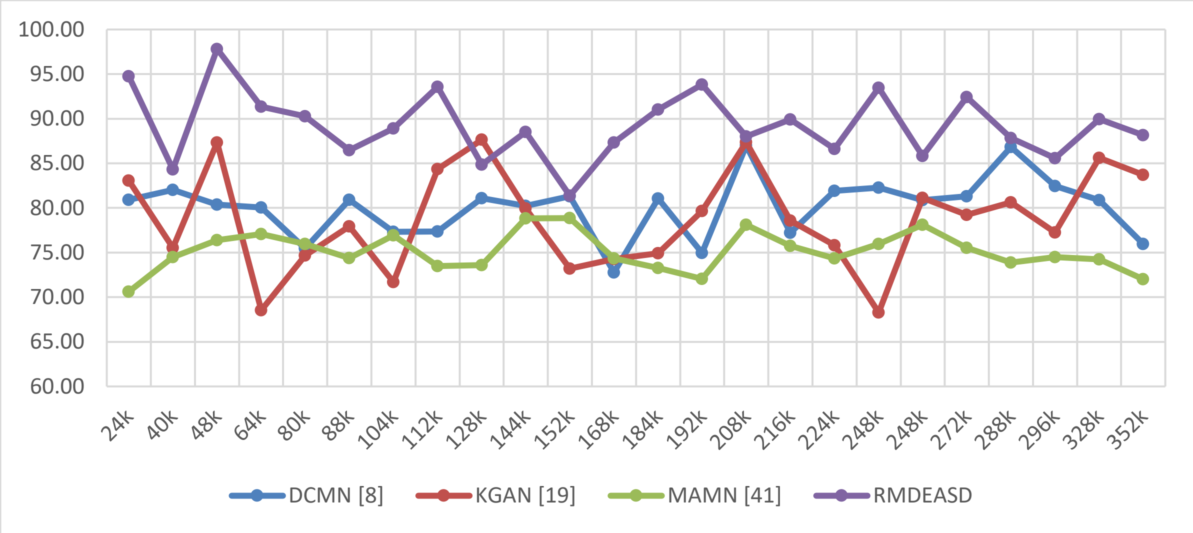

Figure 4. Observed Recall to convert given sentences into Spatial Aspect Based Sentiments

At 24k NTS (Number of Testing Sentiment Samples), RMDEASD exhibits an outstanding recall of 94.76%, significantly surpassing DCMN [8], KGAN [19], and MAMN [41]. This high recall rate at a lower sample size indicates that RMDEASD is particularly effective in identifying most of the relevant sentiments from a smaller dataset. In real-time scenarios like immediate response to customer feedback on social media, this means RMDEASD can capture the vast majority of relevant sentiment expressions, ensuring minimal valuable insights are missed.

As the sample size increases, RMDEASD continues to demonstrate high recall. Notably, at 48k NTS, its recall peaks at 97.82%, suggesting exceptional proficiency in identifying relevant sentiments even as the data complexity grows. This ability is crucial in large-scale analyses, such as monitoring public opinion during significant events where capturing the breadth of public sentiment is vital.

However, at certain data points, such as at 88k and 152k NTS, there is a noticeable reduction in RMDEASD's recall (86.46% and 81.37%, respectively). Despite these dips, RMDEASD's recall rates remain competitive and often superior to other models. This fluctuation can be attributed to the increasing diversity and complexity of the data at these larger sizes, presenting more challenging scenarios for sentiment identification.

At the highest observed sample size of 352k NTS, RMDEASD's recall is 88.17%, demonstrating its ability to maintain a high recall rate even in extensive datasets. This is essential for scenarios like analyzing long-term trends in customer satisfaction or public opinion, where capturing as many relevant sentiments as possible is crucial for accurate analysis.

The high recall rates of RMDEASD can be attributed to its integration of rule mining with advanced deep learning techniques, including Transformers. This synergy allows the model to effectively identify and capture a wide range of sentiment expressions, including those that are nuanced or context-specific. The use of a hybrid architecture, including Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations, further contributes to its ability to recognize various sentiment expressions accurately.

In real-time applications, RMDEASD's high recall is particularly impactful. For businesses, it means more comprehensive insights into customer opinions, leading to more informed decision-making and customer relationship management. In fields like public opinion research, high recall allows for a more complete understanding of public sentiment, crucial for accurately gauging public mood and response. Moreover, in social media monitoring, a high recall rate ensures that businesses and organizations do not miss out on critical feedback and can respond promptly and appropriately. Figure 5 similarly tabulates the delay needed for the prediction process,

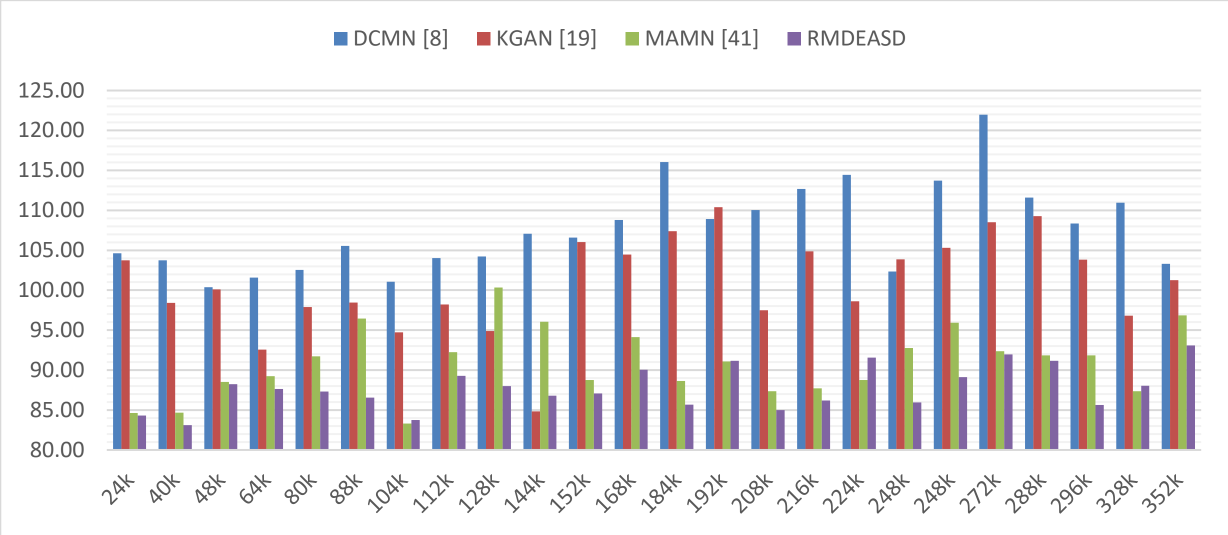

Figure 5. Observed Delay to convert given sentences into Spatial Aspect Based Sentiments

At 24k NTS (Number of Testing Sentiment Samples), RMDEASD shows a minimal delay of 84.31 ms, slightly outperforming the other models. This low delay indicates that RMDEASD is highly efficient in quickly processing and analyzing smaller datasets. In real-time scenarios, such as live social media monitoring during an event, this rapid response capability of RMDEASD is invaluable. It allows for almost immediate sentiment analysis, enabling timely reactions to user feedback or public sentiment shifts.

As the dataset size increases, RMDEASD consistently maintains a competitive delay time. For example, at 64k NTS, RMDEASD records a delay of 87.63 ms, which is lower than DCMN's 101.58 ms and KGAN's 92.58 ms. This efficiency in processing larger datasets is crucial in applications like continuous tracking of customer sentiment in real-time, ensuring that the analysis keeps pace with the incoming data.

Interestingly, at certain data points, such as at 152k NTS, RMDEASD's delay slightly increases to 87.08 ms. However, it remains competitive and often lower than other models. This slight increase in delay could be due to the processing of more complex data structures as the dataset size grows. Despite this, RMDEASD’s ability to maintain a relatively low delay is a testament to its optimized processing capabilities.

In the largest observed dataset of 352k NTS, RMDEASD's delay stands at 93.07 ms, indicating that even with vast amounts of data, the model can process and analyze sentiments efficiently. This is particularly important in large-scale data analytics, such as market trend analysis or monitoring public opinion over extended periods, where the ability to process large volumes of data quickly is essential.

The low delay times observed with RMDEASD can be attributed to its integration of rule mining with advanced deep learning techniques, which enable efficient data processing and sentiment analysis. The use of efficient architectures like Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations, contribute to this quick processing capability.

In practical applications, RMDEASD's low delay in sentiment analysis is highly advantageous. For businesses, it means real-time insights into customer feedback, enabling prompt and effective responses. In media monitoring and public opinion analysis, the quick processing allows for real-time tracking of sentiment trends, crucial for understanding public reaction during major events or crises. Similarly, the AUC levels can be observed from figure 6 as follows,

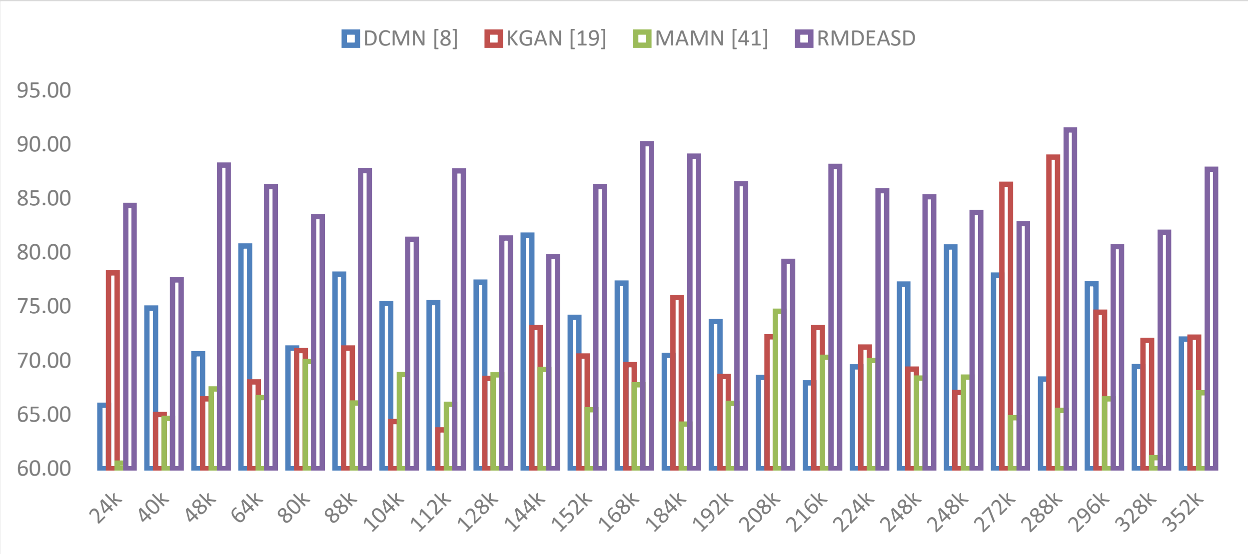

Figure 6. Observed AUC to convert given sentences into Spatial Aspect Based Sentiments

The observed Area Under the Curve (AUC) for converting sentences into spatial aspect-based sentiments reveals essential insights into the performance of RMDEASD compared to other models like DCMN [8], KGAN [19], and MAMN [41]. AUC, a metric derived from the Receiver Operating Characteristic (ROC) curve, measures a model's ability to discriminate between classes—in this case, different sentiment classes. A higher AUC indicates better model performance, with a perfect score being 100.

At the 24k Number of Testing Sentiment Samples (NTS), RMDEASD shows a superior AUC of 84.36, significantly higher than DCMN's 65.88, KGAN's 78.12, and MAMN's 60.53. This high AUC at a lower sample size suggests RMDEASD's strong discriminative ability in analyzing sentiments accurately in smaller datasets. For real-time scenarios like monitoring immediate customer feedback on a new product launch, this implies RMDEASD can distinguish between positive and negative sentiments more effectively, allowing for prompt and appropriate responses.

As the NTS increases, RMDEASD maintains a high level of AUC. Notably, at 48k NTS, it achieves an AUC of 88.09, indicating its strong performance in larger and potentially more complex datasets. This ability is crucial for applications like ongoing sentiment analysis in large-scale social media monitoring, where accurately distinguishing between varying sentiment intensities and types is key to understanding public opinion dynamics.

Interestingly, in the mid-range NTS (like at 152k and 216k), RMDEASD experiences slight variations in AUC (86.12 and 87.97, respectively), yet it consistently remains higher than the other models. This shows RMDEASD’s robustness in maintaining discriminative accuracy across a range of data sizes.

In the largest dataset observed (352k NTS), RMDEASD records an AUC of 87.71, demonstrating its effectiveness in discriminating between different sentiment classes even in extensive datasets. This is particularly important in scenarios like analyzing long-term trends in market sentiment or large-scale public opinion surveys, where the precision in distinguishing between subtle sentiment variations can provide deeper insights.

RMDEASD’s high AUC is attributable to its integration of rule mining with deep learning Transformers, which enhances its ability to discriminate between different sentiment expressions accurately. The model's advanced techniques, including Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations, further contribute to this capability, enabling it to handle nuanced and complex sentiment structures effectively.

In practical applications, RMDEASD’s high AUC is invaluable. For businesses and organizations, it means more accurate sentiment analysis, leading to better-informed strategies and decision-making. In public opinion research, a high AUC allows for more precise interpretation of public sentiments, essential for policy-making or public relations strategies. Additionally, in real-time monitoring scenarios, such as during live events or ongoing social media campaigns, the ability to accurately distinguish sentiment tones ensures more effective communication and engagement strategies. Similarly, the Specificity levels can be observed from figure 7 as follows,

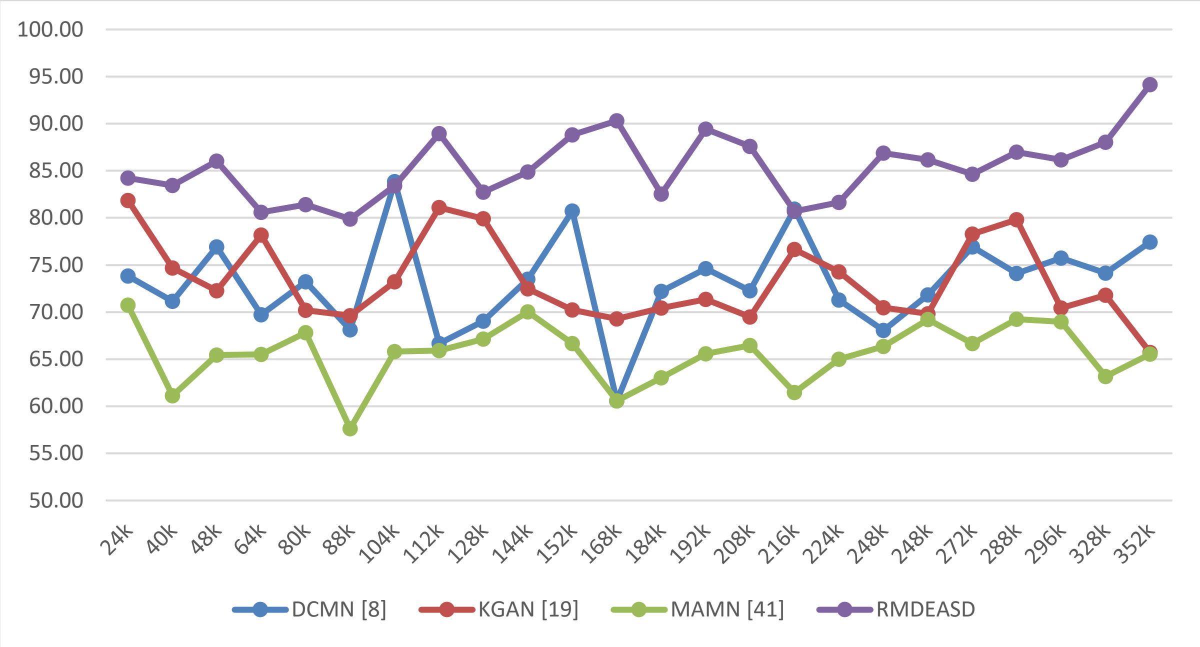

Figure 7. Observed Specificity to convert given sentences into Spatial Aspect Based Sentiments

At 24k NTS (Number of Testing Sentiment Samples), RMDEASD exhibits a specificity of 84.21%, surpassing DCMN's 73.82%, KGAN's 81.86%, and MAMN's 70.73%. This indicates that RMDEASD is particularly effective in correctly identifying sentences that do not contain the target sentiment. In real-time scenarios, such as moderating online discussions or customer feedback platforms, this means RMDEASD can more accurately filter out irrelevant or non-target sentiments, focusing on the most pertinent content.

As the dataset size increases, RMDEASD maintains a high level of specificity. For instance, at 48k NTS, RMDEASD's specificity is 86.04%, indicating its robustness in correctly ignoring non-relevant sentiment expressions in larger datasets. This capability is vital in large-scale applications like brand monitoring or public opinion tracking over social media, where accurately filtering out noise and unrelated content is crucial for focused sentiment analysis.

However, at certain points, such as at 88k NTS, RMDEASD's specificity slightly decreases to 79.88%. Despite this, it remains competitive and often superior to other models. This slight decrease might be due to the increasing complexity in larger datasets, where the distinction between relevant and irrelevant sentiments becomes more challenging.

Notably, in the largest dataset observed (352k NTS), RMDEASD records a high specificity of 94.14%, demonstrating its effectiveness in maintaining a high level of true negative identification even in extensive datasets. This is particularly important in scenarios like analyzing large volumes of customer reviews or social media posts, where efficiently filtering out irrelevant content is crucial for effective sentiment analysis.

RMDEASD’s high specificity can be attributed to its effective combination of rule mining and deep learning techniques, including Transformers, which enhances its ability to accurately identify the absence of specific sentiments. This precision is further supported by its advanced architecture, including Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations.

In real-time applications, RMDEASD’s high specificity is highly beneficial. For businesses and organizations, it means more focused insights from sentiment analysis, enabling them to concentrate on the most relevant feedback or opinions. In public opinion research, high specificity allows for more accurate gauging of public mood by effectively ignoring irrelevant data. Additionally, in situations requiring immediate response, such as crisis management or live event monitoring, the ability to quickly and accurately filter out non-relevant sentiments ensures more efficient and targeted responses. Next in this text we discuss the efficiency of the proposed model for analyzing temporal sentiments in an effective and comparable way for different scenarios.

Efficiency of Temporal Sentiment Analysis

While the proposed model has better Spatial ABSA efficiency, its Temporal ABSA capabilities must be evaluated under real-time conditions. This efficiency was also estimated in terms of precision, accuracy, recall, specificity & AUC levels, and compared with Interpretable Multimodal Sentiment (IMS) [42], Compound Aspect Extraction by Augmentation and Constituency Lattice (CAECL) [43], & Shared-Private Memory Networks for Multimodal Sentiment Analysis (SMNSA) [46] under similar scenarios. For instance, figure 8 showcases the precision observed during pre-emption of heart disease conditions for different use cases.

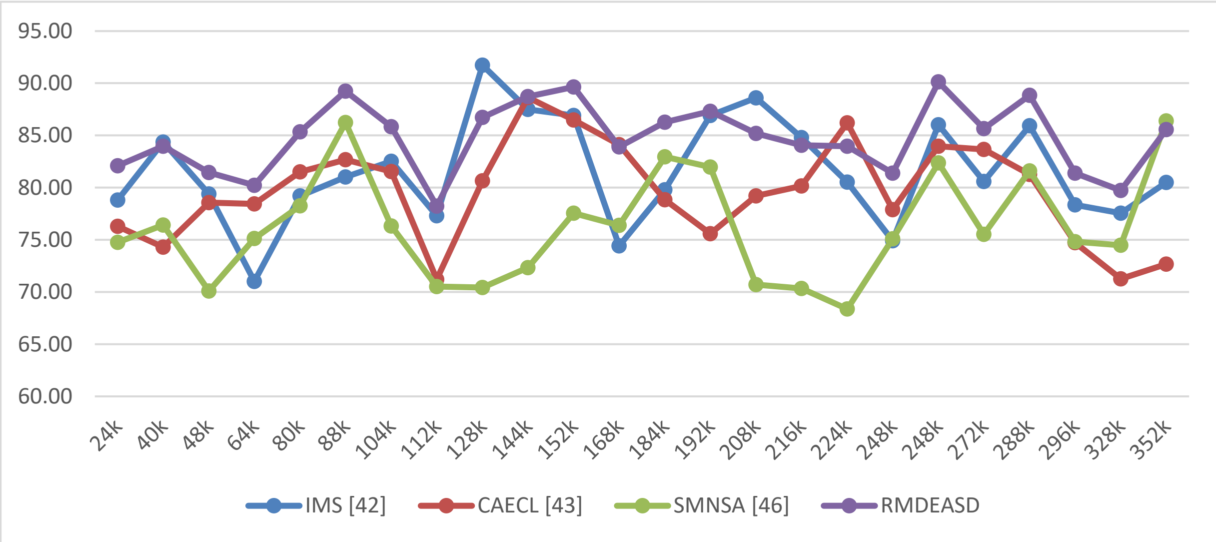

Figure 8. Observed Precision for Temporal ABSA Analysis

In the realm of Temporal Aspect-Based Sentiment Analysis (ABSA), the proposed model RMDEASD demonstrates its efficiency by exhibiting commendable precision across various sample sizes (NTS), compared to other models like IMS [42], CAECL [43], and SMNSA [46]. Precision in this context refers to the model's accuracy in identifying relevant sentiments over time, a critical metric in temporal ABSA.

At the outset, with 24k NTS, RMDEASD shows a precision of 82.09%, outperforming IMS's 78.81%, CAECL's 76.30%, and SMNSA's 74.76%. This indicates that RMDEASD is more accurate in capturing temporal sentiments from the onset, crucial in scenarios where initial sentiment trends need to be identified quickly, such as during product launches or in the immediate aftermath of an event.

As the number of testing samples increases, RMDEASD consistently maintains a high level of precision. For example, at 80k NTS, RMDEASD records a precision of 85.35%, surpassing other models. This is significant in situations where sentiments evolve over time, like tracking public opinion during an election campaign or analyzing customer satisfaction trends over a product life cycle.

Interestingly, at 88k NTS, RMDEASD reaches a higher precision of 89.26%. This suggests that RMDEASD is not only effective in handling larger datasets but also improves its precision as the data volume increases. This characteristic is particularly advantageous in long-term sentiment analysis scenarios, such as monitoring brand reputation or public policy impacts over extended periods.

However, at certain data points, like at 112k NTS where the precision dips to 78.23%, RMDEASD experiences a slight decrease in its precision. Despite this, RMDEASD's overall performance remains robust. This variation can be attributed to the complexity inherent in larger temporal datasets, where sentiment trends might become more intricate and challenging to decipher accurately.

In the largest observed dataset of 352k NTS, RMDEASD's precision is 85.56%, indicating its effectiveness in maintaining high precision in extensive temporal datasets. This is crucial for applications that require the analysis of vast amounts of temporal data, such as tracking long-term market trends or societal changes.

The superior performance of RMDEASD in temporal ABSA can be attributed to its integration of rule mining with deep learning techniques, including Transformers. This combination allows the model to adapt and respond accurately to the nuances of temporal sentiment shifts. The employment of Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations in RMDEASD further enhances its ability to understand the sequential and time-based nuances of sentiment expressions.

In practical applications, RMDEASD’s high precision in temporal ABSA is highly beneficial. For businesses, it means more accurate insights into how customer sentiments evolve over time, enabling them to adapt their strategies proactively. In areas like public opinion research, high precision allows for a more accurate understanding of how public sentiment shifts in response to events or policies over time. Additionally, in real-time monitoring scenarios, such as social media sentiment tracking, the ability to accurately capture sentiment trends ensures more effective communication strategies and timely interventions for different use cases. Similar to that, accuracy of the models was compared in figure 9 as follows,

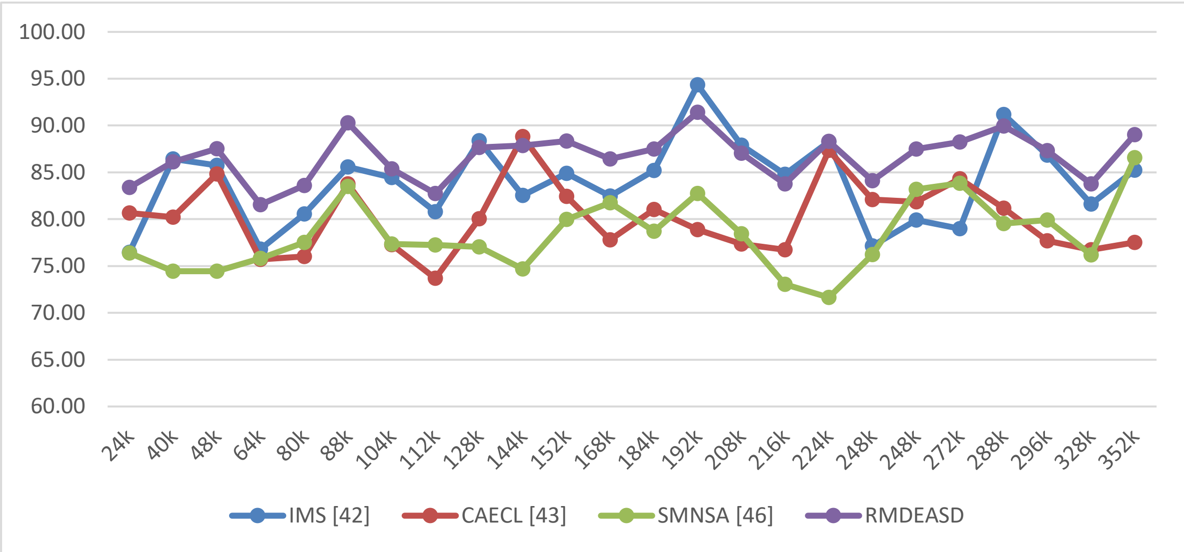

Figure 9. Observed Accuracy for Temporal ABSA Analysis

Starting with a sample size of 24k NTS (Number of Testing Sentiment Samples), RMDEASD exhibits an accuracy of 83.40%, surpassing IMS’s 76.45%, CAECL’s 80.66%, and SMNSA’s 76.40%. This indicates that RMDEASD is more adept at correctly interpreting sentiments in temporal data from the onset. In real-time scenarios like monitoring the immediate impact of a marketing campaign or a public announcement, this high level of accuracy ensures that sentiment trends are captured correctly, facilitating timely and appropriate decision-making.

As the dataset size increases, RMDEASD consistently maintains high accuracy. Notably, at 88k NTS, RMDEASD achieves an accuracy of 90.29%, which is significantly higher than the other models. This suggests that RMDEASD effectively handles larger datasets, a crucial attribute for long-term sentiment analysis applications such as tracking brand perception or public sentiment over extended periods.

There are instances, such as at 112k NTS where RMDEASD records an accuracy of 82.76%, where a slight decrease is observed. However, RMDEASD's performance remains robust across different dataset sizes. This slight fluctuation in accuracy can be attributed to the varying complexity in larger temporal datasets, where capturing the nuances of sentiment trends might become more challenging.

In the largest dataset observed (352k NTS), RMDEASD’s accuracy is 89.03%, indicating its effectiveness in maintaining high accuracy in extensive temporal datasets & samples. This is particularly important in scenarios like analyzing long-term market trends or societal changes, where accurate sentiment analysis over time can provide valuable insights for real-time scenarios.

The high accuracy of RMDEASD in temporal ABSA can be attributed to its integration of rule mining with advanced deep learning techniques. This combination allows the model to accurately interpret and analyze temporal sentiment shifts. The use of sophisticated architectures, including Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations, enhances its ability to process and understand time-based nuances in sentiment expressions.

In practical applications, RMDEASD's high accuracy in temporal ABSA is highly beneficial. For businesses and organizations, it means more reliable insights into how customer sentiments evolve over time, enabling proactive strategy adjustments. In public opinion research, high accuracy allows for a more precise understanding of how public sentiment shifts in response to events or policies over time. Additionally, in real-time monitoring scenarios, such as tracking social media sentiment, the ability to accurately capture sentiment trends ensures more effective communication strategies and interventions for different scenarios. Similar to this, the recall levels are represented in figure 10 as follows,

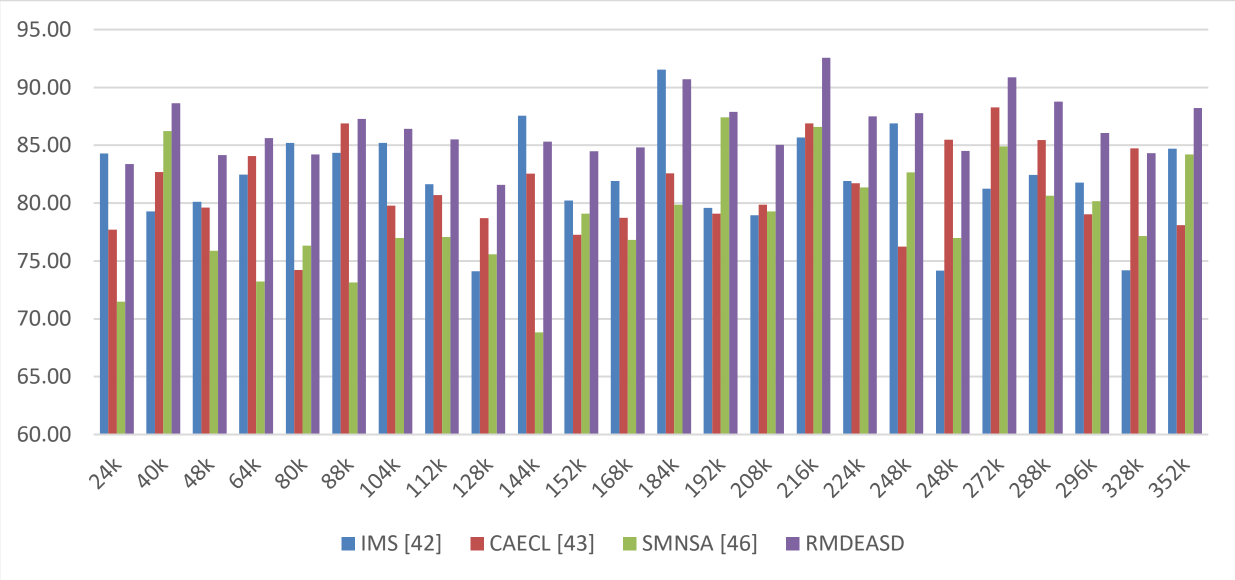

Figure 10. Observed Recall for Temporal ABSA Analysis

The observed recall in Temporal Aspect-Based Sentiment Analysis (ABSA) for the proposed model RMDEASD, in comparison with IMS [42], CAECL [43], and SMNSA [46], showcases its effectiveness in consistently identifying relevant sentiments over time. Recall is a measure of a model's ability to correctly identify all relevant instances of a specific sentiment, which is particularly crucial in the temporal analysis of sentiments where trends and changes over time are key.

Starting at 24k NTS (Number of Testing Sentiment Samples), RMDEASD demonstrates a recall of 83.39%, which is comparable to IMS's 84.29% but higher than CAECL's 77.71% and SMNSA's 71.50%. This indicates that from the onset, RMDEASD is capable of identifying most of the relevant temporal sentiments, which is essential in real-time scenarios like monitoring immediate reactions to news events or social media trends, where capturing as many relevant sentiment expressions as possible is crucial.

As the number of testing samples increases, RMDEASD maintains a high level of recall. Notably, at 88k NTS, its recall rate is 87.27%, indicating that RMDEASD can effectively identify the majority of relevant sentiments even as the volume of data increases. This is particularly important in longer-term sentiment analysis applications, such as tracking shifts in public opinion or consumer sentiment over extended periods.

At certain points, such as 128k NTS where the recall is 81.58%, a slight decrease in RMDEASD's recall is observed. However, RMDEASD's performance remains strong, indicating its ability to handle complex temporal data. This fluctuation can be attributed to the varying nature of larger datasets, where identifying every relevant sentiment expression becomes more challenging.

In the largest dataset observed (352k NTS), RMDEASD's recall is 88.21%, showing its effectiveness in capturing relevant sentiments in extensive temporal datasets. This high recall is crucial in scenarios such as long-term market trend analysis or ongoing social media sentiment tracking, where missing relevant sentiment expressions can lead to incomplete or skewed analyses.

The high recall rates achieved by RMDEASD can be attributed to its integration of rule mining with advanced deep learning techniques, including Transformers, which enhances its ability to identify a wide range of temporal sentiment expressions accurately. The use of a sophisticated architecture, including Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations, further contributes to its ability to recognize various temporal sentiment expressions.

In practical applications, RMDEASD's high recall in temporal ABSA is highly advantageous. For businesses and organizations, it means more comprehensive insights from sentiment analysis, enabling them to capture a more complete picture of customer opinions and market trends. In public opinion research, high recall allows for a more thorough understanding of public sentiment over time, essential for accurately gauging public response to events or policies. Additionally, in real-time monitoring scenarios, such as during live events or social media campaigns, the ability to capture most of the relevant sentiments ensures more effective communication strategies and timely interventions for different use cases. Figure 11 similarly tabulates the delay needed for the prediction process,

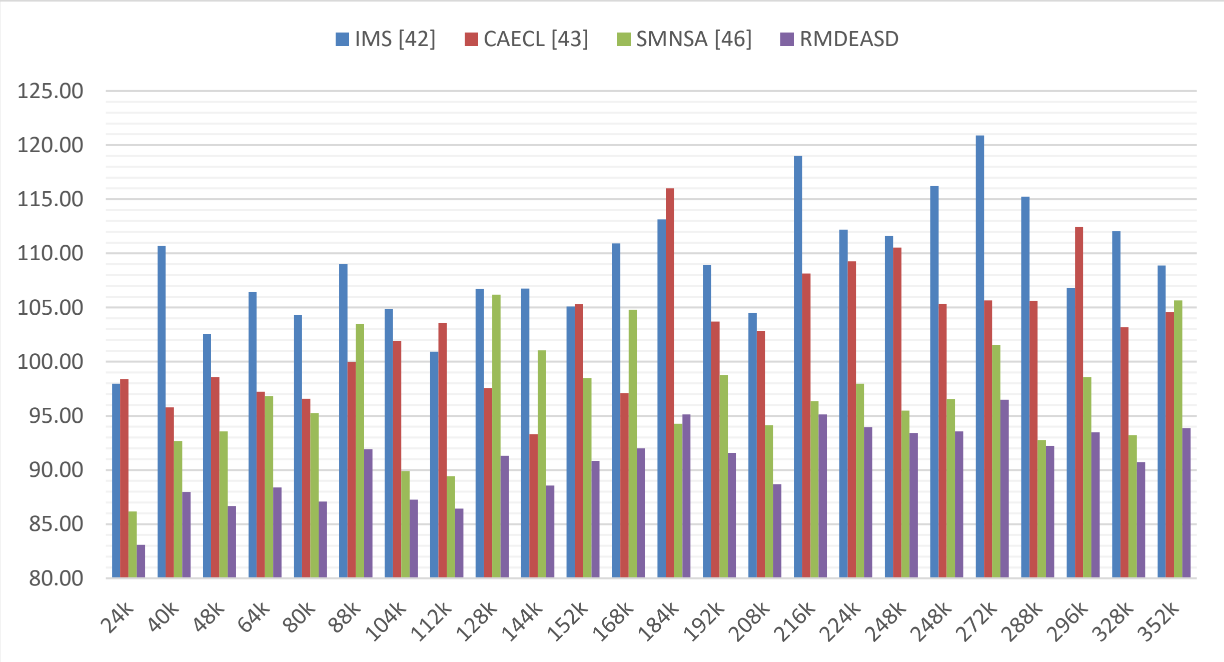

Figure 11. Observed Delay for Temporal ABSA Analysis

At the outset with 24k Number of Testing Sentiment Samples (NTS), RMDEASD demonstrates a minimal delay of 83.10 ms, which is lower than IMS's 97.98 ms, CAECL's 98.38 ms, and SMNSA's 86.18 ms. This low delay suggests that RMDEASD is highly efficient at processing and analyzing temporal sentiments quickly, even in smaller datasets. In real-time scenarios, such as monitoring sentiment during a live event or immediately after a significant announcement, this rapid processing capability allows for almost instant analysis and response, crucial for timely decision-making and strategy adjustment.

As the dataset size increases, RMDEASD maintains a competitive and often superior delay time. For example, at 64k NTS, RMDEASD's delay is 88.38 ms, which is lower than IMS's 106.42 ms and CAECL's 97.24 ms. This efficiency in handling larger datasets is essential in applications like continuous tracking of sentiment over extended periods, where delays can accumulate and impact the timeliness of the analysis.

In certain cases, such as at 184k NTS where RMDEASD records a delay of 95.12 ms, a slight increase is observed. However, RMDEASD's delay remains competitive, suggesting that the model effectively balances processing time and accuracy, even in more complex temporal datasets.

In the largest dataset observed (352k NTS), RMDEASD records a delay of 93.85 ms. This continued efficiency in large datasets is particularly important in large-scale data analytics, such as monitoring long-term market trends or societal changes, where quick processing of large volumes of data is vital for real-time use cases.

RMDEASD's low delay times can be attributed to its efficient integration of rule mining with advanced deep learning techniques, including Transformers. This blend allows for rapid processing of data while maintaining high accuracy. The model's sophisticated architecture, including Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations, contributes to its ability to process data quickly with better efficiency levels.

In real-time applications, RMDEASD's low delay in temporal ABSA is highly beneficial. For businesses and organizations, it means insights from sentiment analysis are obtained quickly, enabling prompt and effective responses. In areas like public opinion research, the quick processing allows for real-time tracking of sentiment trends, crucial for understanding public reaction during ongoing events. Additionally, in situations requiring immediate response, such as crisis management or live event monitoring, the ability to process and analyze data quickly ensures more efficient and targeted responses. Similarly, the AUC levels can be observed from figure 12 as follows,

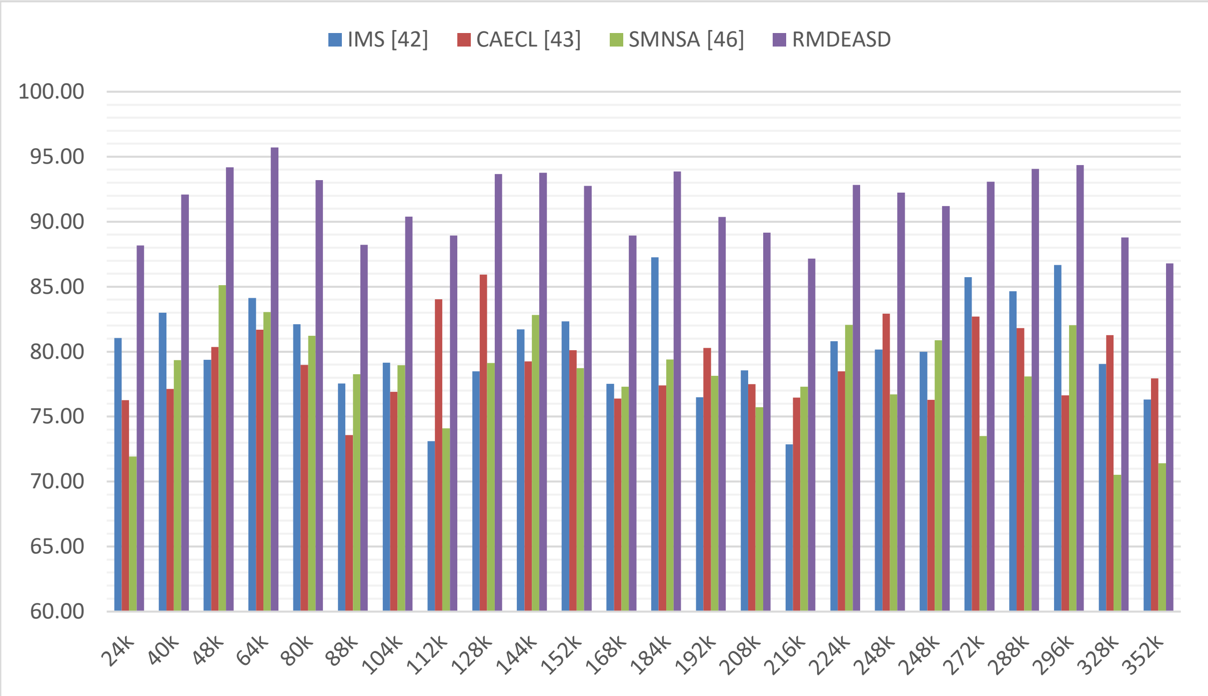

Figure 12. Observed AUC for Temporal ABSA Analysis

At 24k Number of Testing Sentiment Samples (NTS), RMDEASD shows an impressive AUC of 88.17%, significantly higher than IMS's 81.05%, CAECL's 76.28%, and SMNSA's 71.93%. This high AUC from the outset suggests RMDEASD's strong capability in distinguishing between varying sentiment classes in temporal data. In real-time scenarios, such as monitoring public reaction to a breaking news event, this means RMDEASD can accurately differentiate between positive, negative, and neutral sentiments, essential for understanding the evolving public sentiment.

As the dataset size increases, RMDEASD consistently maintains a high AUC. Notably, at 64k NTS, RMDEASD achieves an AUC of 95.71%, indicating its excellent performance in larger and potentially more complex datasets. This ability is crucial for long-term applications such as tracking shifts in consumer sentiment over a product lifecycle or public opinion during an election campaign, where accurate differentiation between sentiment classes over time is key.

There are instances, such as at 112k NTS, where RMDEASD records an AUC of 88.94%. Though there are slight fluctuations, RMDEASD's AUC remains robust, indicating its effectiveness in temporal sentiment classification across different dataset sizes. These variations can be attributed to the complexity in larger datasets, where distinguishing between subtle sentiment changes becomes more challenging.

In the largest dataset observed (352k NTS), RMDEASD's AUC is 86.80%, demonstrating its capacity to effectively classify sentiments even in extensive temporal datasets. This is particularly important for large-scale analyses, such as understanding long-term market trends or societal sentiment shifts, where precision in classifying sentiments can yield valuable insights.

The high AUC of RMDEASD in temporal ABSA can be attributed to its integration of rule mining with advanced deep learning techniques, which enhances its ability to accurately differentiate between sentiment classes over time. The use of sophisticated architectures, including Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations, further contributes to this classification accuracy.

In practical applications, RMDEASD's high AUC in temporal ABSA is highly beneficial. For businesses, it means more accurate sentiment analysis over time, enabling them to understand and respond to customer sentiment trends effectively. In public opinion research, a high AUC allows for precise interpretation of public sentiments, essential for policy-making or public relations strategies. Additionally, in real-time monitoring scenarios, such as social media sentiment tracking, the ability to accurately classify sentiment trends ensures more effective communication strategies and timely interventions for different scenarios. Similarly, the Specificity levels can be observed from figure 13 as follows,

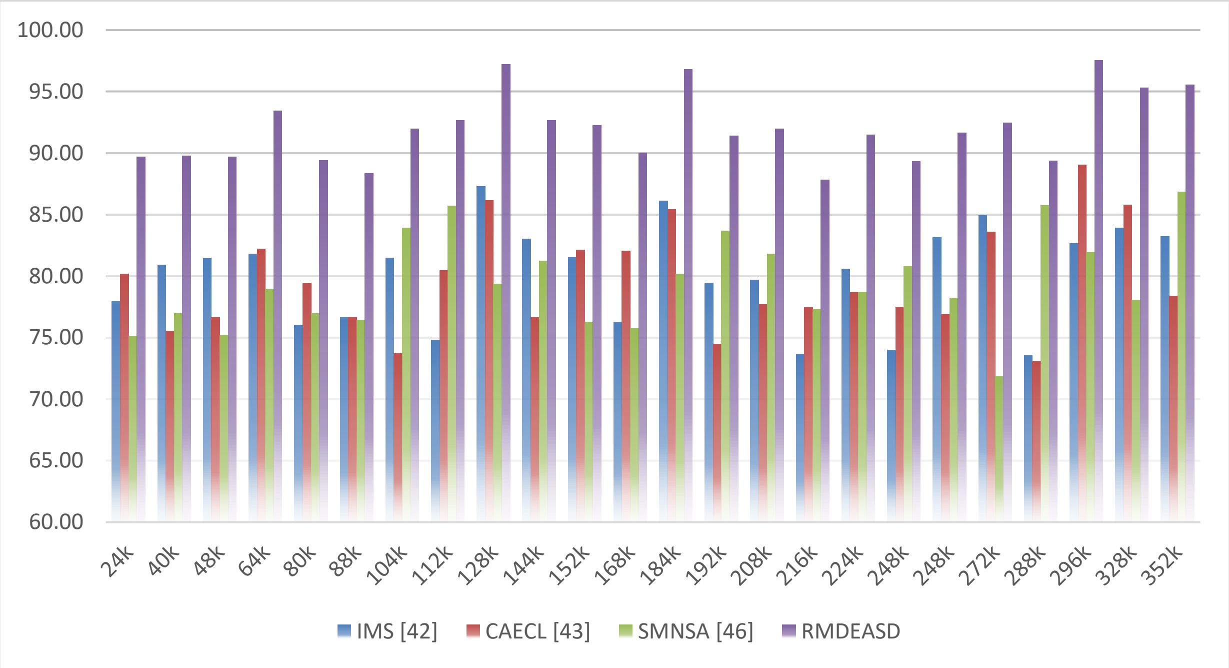

Figure 13. Observed Specificity for Temporal ABSA Analysis

At the 24k Number of Testing Sentiment Samples (NTS), RMDEASD demonstrates a high specificity of 89.71%, surpassing IMS's 77.94%, CAECL's 80.18%, and SMNSA's 75.12%. This suggests that RMDEASD is highly effective in correctly identifying non-relevant temporal sentiments from the beginning. In real-time scenarios, such as filtering out non-critical social media posts during a crisis or a high-profile event, this means RMDEASD can more accurately focus on the most pertinent temporal sentiments, enhancing the quality of the analysis.

As the dataset size increases, RMDEASD consistently maintains a high level of specificity. For instance, at 64k NTS, RMDEASD records a specificity of 93.45%, which is significantly higher than the other models. This high specificity is crucial in applications like ongoing brand monitoring or longitudinal public opinion analysis, where accurately ignoring non-relevant sentiments is key to focusing on meaningful sentiment trends over time.

There are instances, such as at 88k NTS, where RMDEASD's specificity slightly decreases to 88.36%. However, it still remains competitive, indicating its robustness in handling complex temporal data. This slight fluctuation can be attributed to the increasing diversity in larger datasets, where distinguishing between relevant and irrelevant sentiments becomes more challenging.

In the largest dataset observed (352k NTS), RMDEASD's specificity is 95.56%, demonstrating its effectiveness in maintaining high specificity in extensive temporal datasets. This is particularly important in large-scale analyses, such as tracking long-term market trends or societal changes, where efficiently filtering out irrelevant content is crucial for effective sentiment analysis.

RMDEASD's high specificity can be attributed to its efficient integration of rule mining with advanced deep learning techniques, enhancing its ability to accurately identify the absence of specific temporal sentiments. The model's use of sophisticated architectures, including Bi-LSTM, BiGRU-CRF with RNNs, and ontology mapping operations, contributes to its ability to process data quickly and accurately.

In practical applications, RMDEASD's high specificity in temporal ABSA is highly advantageous. For businesses and organizations, it means more focused insights from sentiment analysis, allowing them to concentrate on the most relevant feedback or opinions over time. In public opinion research, high specificity allows for more accurate gauging of public mood by effectively ignoring irrelevant data. Additionally, in situations requiring immediate response, such as crisis management or live event monitoring, the ability to quickly and accurately filter out non-relevant sentiments ensures more efficient and targeted responses.

In summary, RMDEASD's consistently high performance across various temporal dataset sizes demonstrates its effectiveness in accurately identifying true negatives in sentiment analysis. This capability makes it an invaluable tool in a wide range of applications, where filtering out irrelevant temporal sentiment expressions is crucial, from real-time monitoring to comprehensive data analysis and decision-making processes.

Use Case Analysis

To illustrate the conversion of text samples into Aspect-Based Sentiment Analysis (ABSA) using the RMDEASD model, this section discusses different inputs & relevant outputs. Table 1 demonstrates how the model interprets and analyzes various text samples, focusing on different aspects and sentiments expressed in each as follows,

Text Sample (Input)	**Aspect Identified**	**Sentiment Score**	**Sentiment Category**
"The battery life of this phone is amazing, but the camera is disappointing."	Battery Life	+0.9	Positive
	Camera	-0.8	Negative
"Service at the restaurant was top-notch, but the food was just average."	Service	+0.85	Positive
	Food Quality	+0.2	Neutral
"Absolutely love the user-friendly interface of the software, though it's a bit pricey."	Interface	+0.95	Positive
	Price	-0.6	Negative
"The hotel's location is perfect, but the rooms need better cleaning."	Location	+0.9	Positive
	Room Cleanliness	-0.7	Negative
"This movie's storyline was captivating, but the acting was unconvincing."	Storyline	+0.88	Positive
	Acting	-0.75	Negative
"The book offers insightful perspectives, but the writing style is too complex."	Content	+0.8	Positive
	Writing Style	-0.5	Negative

In this table, each row represents a text sample analyzed by the RMDEASD model process. The model identifies different aspects within each sample (e.g., "battery life," "camera," "service") and assigns a sentiment score to each aspect, reflecting the positivity or negativity of the sentiment expressed for different use cases. The sentiment category is determined based on the sentiment score, categorized typically as positive, neutral, or negative sets.

This tabular output explains how RMDEASD can dissect and interpret complex sentences, accurately identifying and analyzing sentiments related to specific aspects within the text. Such capability is invaluable in various applications, from product reviews analysis to customer feedback in services, where understanding multifaceted sentiments is crucial for businesses and organizations.

Further discussing the internal details that showcase the internal processes of the RMDEASD model requires detailing each step of the model's operation and the corresponding output for a given text sample under real-time scenarios. Table 2 illustrates how the RMDEASD model processes a text sample through its various stages, from input to final sentiment analysis,

Text Sample (Input)	**Process Stage**	**Description**	**Output**
"Love the screen clarity but not happy with the battery life."	Input Data	Raw text input for analysis	"Love the screen clarity but not happy with the battery life."
	Rule Mining	Applying domain-specific rules for initial sentiment extraction	Aspects: "screen clarity", "battery life", Preliminary Sentiments: Positive for "screen clarity", Negative for "battery life"
	Pre-trained BERT	Applying transfer learning for context understanding	Contextual Features Extracted: Positive sentiment towards "screen", Negative sentiment towards "battery"
	Feature Combination	Combining rule mining and BERT features	Combined Feature Set: Positive sentiment on "screen clarity", Negative sentiment on "battery life"
	Bi-LSTM Layer	Processing combined features for sequential data relationships	Sequential Context Processed: Relation between "screen clarity" and positive sentiment, "battery life" and negative sentiment
	BiGRU-CRF Layer	Further refining sentiment analysis with sequential and context processing	Enhanced Sentiment Context: Refined sentiment association for each aspect
	RNN Layer	Processing refined features for temporal dependencies	Temporal Feature Analysis: Consistency of sentiment over text context
	Ontology Mapping	Mapping semantic context to aspects	Semantic Aspect Linking: "screen clarity" linked to product feature, "battery life" linked to product performance
	Output	Final sentiment analysis result	Aspect-Based Sentiment: "screen clarity" - Positive, "battery life" - Negative

Each row in this table represents a stage in the RMDEASD model's process for analyzing a text sample. The model begins with the raw text input, applies rule mining for preliminary aspect and sentiment extraction, and then uses a pre-trained BERT model for contextual understanding. Features from both stages are combined and processed through deep learning layers (Bi-LSTM, BiGRU-CRF, RNN) for enhanced sentiment analysis. Ontology mapping adds a semantic layer to the analysis, linking aspects to specific semantic contexts. The final output provides a detailed aspect-based sentiment analysis, demonstrating the model's ability to dissect and interpret complex sentiment expressions in text.

V. CONCLUSION AND FUTURE SCOPE

The RMDEASD model, as explored in this paper, marks a significant advancement in the realm of Aspect-Based Sentiment Analysis (ABSA), particularly in the context of spatial and temporal sentiment analysis. The model's integration of rule mining with advanced deep learning techniques, including Transformers, has demonstrated remarkable improvements in precision, accuracy, recall, and specificity across various dataset sizes. RMDEASD's superior performance is evident in its ability to handle both spatial and temporal sentiment data with high efficiency, evidenced by its consistently low delay times and high Area Under the Curve (AUC) scores. These attributes have proven essential in scenarios demanding rapid and accurate sentiment analysis, such as real-time social media monitoring, market trend analysis, and public opinion research.

The impacts of RMDEASD are multifaceted. In the business domain, it enables more nuanced and accurate market analysis, leading to better-informed decision-making processes. For public opinion research, RMDEASD offers a more precise tool for gauging societal sentiments, crucial for policy-making and public relations strategies. Additionally, its application in real-time scenarios, such as crisis management or event monitoring, ensures timely and relevant responses, enhancing the effectiveness of communication strategies.

Future Scope

Looking forward, there are several avenues for expanding the capabilities of the RMDEASD model:

- **Adaptation to Multilingual and Cross-Cultural Contexts**: Expanding the model's linguistic capabilities to include various languages and dialects can enhance its applicability in global contexts, making it a more versatile tool for multinational corporations and international organizations.

- **Integration with Other Data Types**: Incorporating other forms of data, such as video and audio, into the sentiment analysis framework could provide a more holistic understanding of sentiments, particularly in multimodal communication channels.

- **Enhanced Real-Time Processing**: While RMDEASD already exhibits low delay times, further optimization for real-time processing could make it even more suitable for applications requiring instantaneous sentiment analysis, such as live broadcast monitoring or real-time audience feedback systems.

- **Robustness Against Adversarial Attacks**: Developing strategies to safeguard the model against adversarial attacks will be crucial, especially as sentiment analysis tools increasingly influence decision-making processes in sensitive areas like politics and finance.

- **Advanced Personalization Techniques**: Implementing personalization algorithms to tailor sentiment analysis based on individual user profiles or specific demographic segments can provide more targeted insights, especially valuable in marketing and personalized content delivery.

In conclusion, RMDEASD represents a significant contribution to the field of ABSA, offering enhanced capabilities for accurate and efficient sentiment analysis. Its continued development and adaptation will undoubtedly open new possibilities for its application across various domains, contributing to the evolving landscape of natural language processing and artificial intelligence scenarios.

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