GROUP 12 - PROJECT PROGRESS

Domain-Specific Sentiment Analysis in Textual Feedback

AI-Powered Aspect Detection and Sentiment Analysis for Textual Feedback and Reviews

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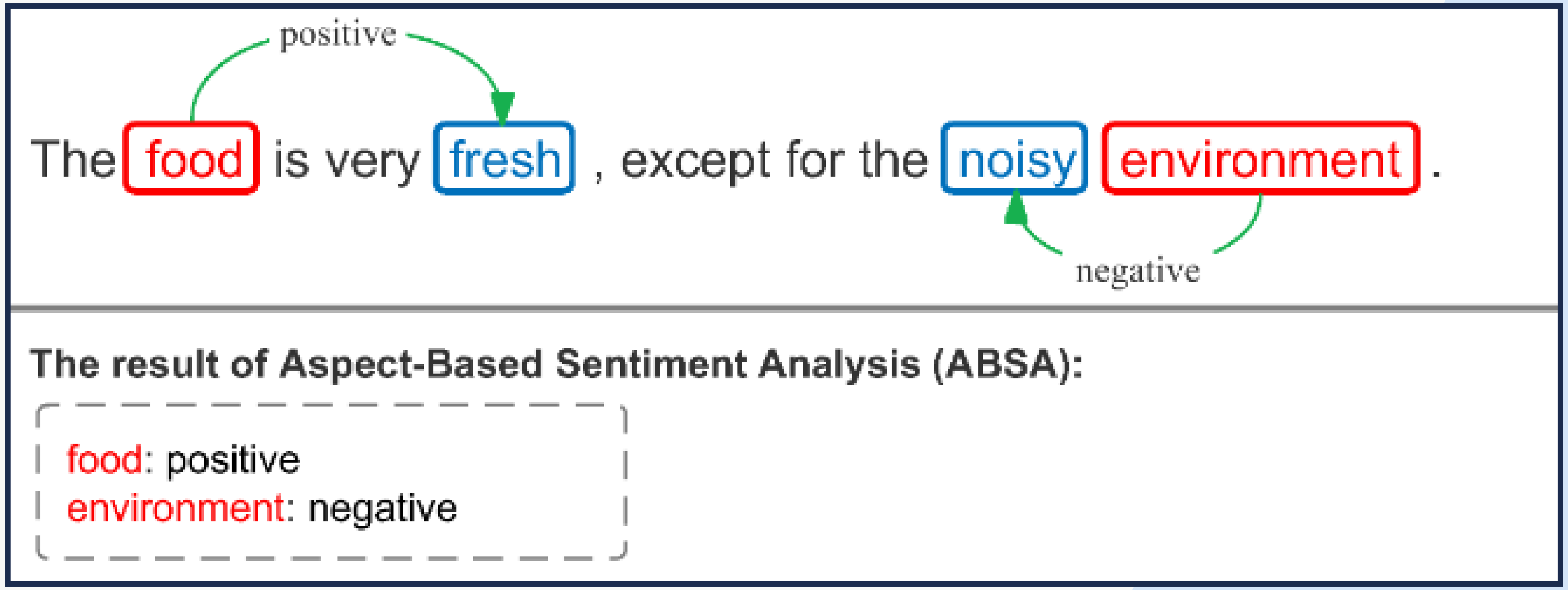
Problem Statement

The Emojot platform struggles with high costs and low accurate sentiment analysis due to using the Open AI, AWS Comprehend , and Auto ML API calls.

Our project aims to develop an **AI solution** to accurately identify sentiments in domain-specific text reviews. Through our **cost-effective** solution, we aim to **reduce expenses while improving accuracy** and enabling better decision-making and user engagement within the Emojot platform.

What is Aspect Based Sentiment Analysis ?

Aspect-Based Sentiment Analysis (ABSA) is a text analysis technique that **breaks down** textual data and **determines** its **sentiment** based on **specific aspects**. This method analyzes consumer feedback by connecting sentiments to various aspects of a product or service.

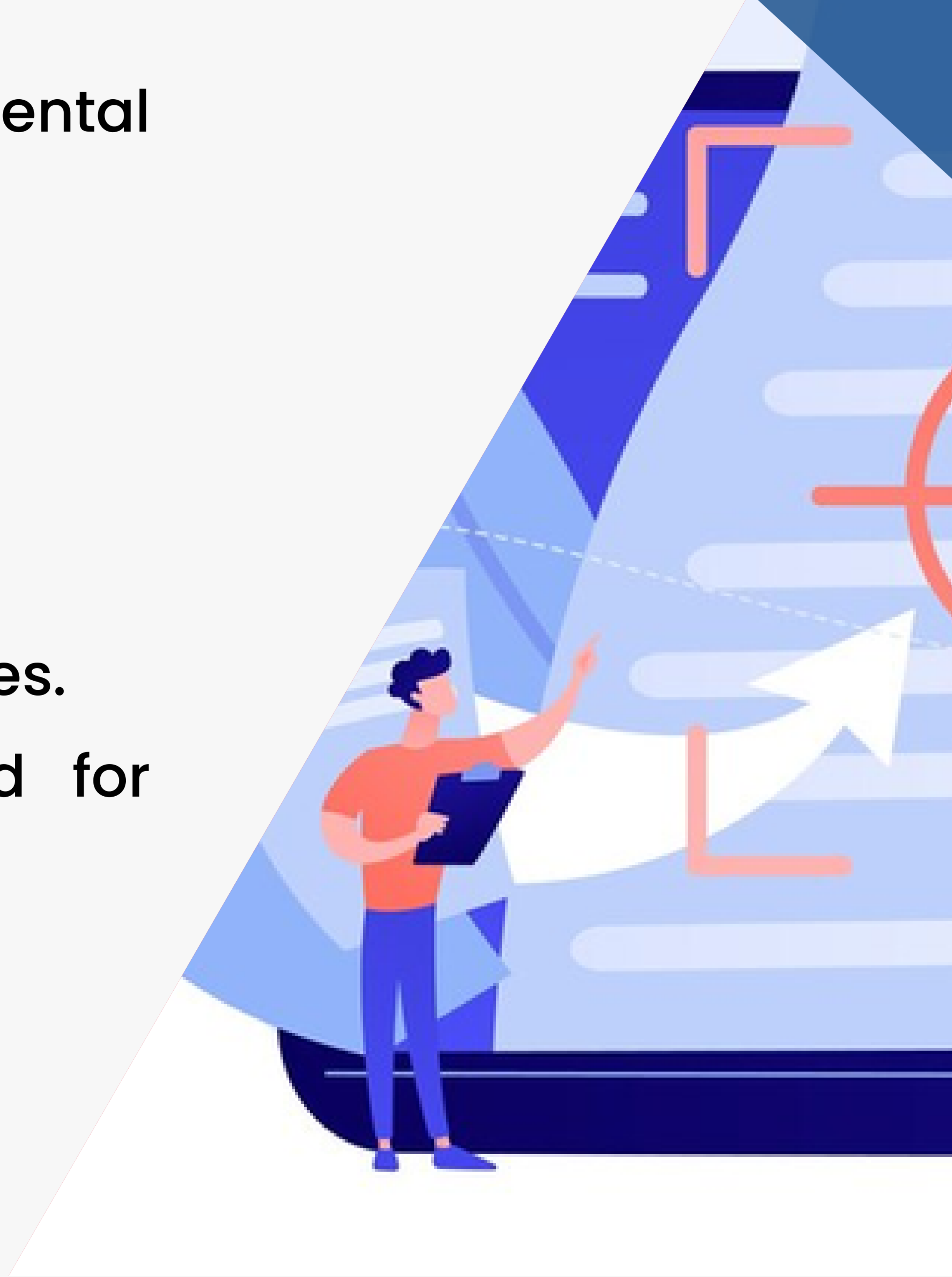


Project Objectives

- Investigate and assess the key differences, advantages, and disadvantages of sentiment analysis techniques.
- Develop a model that can achieve a high accuracy in recognizing aspects from sentences related to a specific domain within textual reviews
- Build a machine learning model with a high accuracy to identify the polarity of sentences in sentiment analysis within the Emojot platform.
- Develop a user-friendly interface.

Project Scope

- Research will be limited to “aspect-based” sentimental analysis methods.
- Reviews are considered under a specific domain.
- Aspects are decided by the clients.
- Only English reviews are analyzed.
- positive, neutral, and negative are the sentiment polarities.
- The interface for the application will be developed for demonstration purposes.



Progress Evolution

APRIL

JUNE

AUGUST

MERCon 2024
Under Review

ICTer 2024
Under Review

Literature Review

Our Main Goals

High Accuracy Model Generation

Cost Effective Implementation

Research Gap

Less research is done in the joint(ATE+ASC) task hybrid model development for aspect based sentiment analysis.

First Objective

- Investigate and assess the key differences, advantages, and disadvantages of sentiment analysis techniques.

Literature Review

Overview of Tasks for Aspect-Based Sentiment Analysis

Task	Input	Output
Aspect Term Extraction (ATE)	S_i	a^1, a^2
Aspect Sentiment Classification (ASC)	$S_i + a^1, S_i + a^2$	sp^1, sp^2
Joint Task (ATE + ASC)	S_i	$(a^1, sp^1), (a^2, sp^2)$

S_i: The price was high, but the restaurant was breathtaking.

Task	Input	Output
Aspect Term Extraction (ATE)	S_i	$price, restaurant$
Aspect Sentiment Classification (ASC)	$S_i + price, S_i + restaurant$	$Negative, Positive$
Joint Task (ATE + ASC)	S_i	$(price, Negative), (restaurant, Positive)$

Literature Review

More than 70 single task models were found.

- **LSTM**
- **BERT**
- **DeBERTa**
- **RoBERTa**
- **Other Models**

F1 Scores of Models Evaluated on the SemEval 2014 Benchmark.

Model	F1 Score (%)							
	Res-14		Lap-14		Res-15		Res-16	
	AE	SP	AE	SP	AE	SP	AE	SP
InstructABSA [7]	**92.10**	85.17	**92.30**	81.56	**76.64**	84.50	**80.32**	89.43
GPT2(med) [98]	75.94	–	82.04	–	–	–	–	–
GRACE [96]	85.45	–	87.93	–	–	–	–	–
LCF-ATEPC-CDM [94]	89.78	85.88	85.29	79.84	–	–	–	–
ASCNN [99]	–	73.10	–	66.72	–	58.90	–	70.43
ASGCN [99]	–	70.48	–	68.06	–	60.78	–	70.29
MCRF-SA [100]	–	73.78	–	74.23	–	61.59	–	75.92
KaGRMN-DSG [101]	–	81.98	–	79.42	–	–	–	–
RAM [70]	–	68.54	–	68.43	–	–	–	–
TN (BiLSTM+C2A+Pas) [53]	–	65.75	–	65.34	–	–	–	–
MGAN [53]	–	71.48	–	71.42	–	–	–	–
CNN-ASP [103]	–	65.11	–	65.31	–	–	–	–
PRET+MULT [102]	–	69.73	–	67.46	–	68.74	–	–
MemNet [68]	–	69.94	–	65.17	–	58.28	–	65.99
IAN [58]	–	70.09	–	67.38	–	52.65	–	55.21
BART-ABSA [97]	87.07	–	83.52	–	75.48	–	–	–
LSAT [95]	–	90.86	–	86.31	–	–	–	–
DeBERTaV3 [6] [90]	–	83.06	–	79.45	–	73.76	–	73.59
ABSA-DeBERTa[93]	–	89.46	–	82.76	–	–	–	–
DeBERTa-V3-base-absa-v1.1* [92, 104]	–	**90.94**	–	**90.32**	–	**89.55**	–	**84.91**
LSA-X-DeBERTa [91]	–	87.02	–	84.41	–	81.29	–	84.87

Note ∗ : The F1-scores for the DeBERTa-v3-base-absa-v1.1 model was calculated by us separately.

BERT [5]	–	71.91	79.28	71.94	–	–	74.10	–
BERT-DK [75]	77.02	75.45	83.55	73.72	–	–	–	–
BERT-SPC [76] [80]	–	76.98	–	75.03	–	–	–	–
BERT-MRC [77]	74.21	74.97	81.06	74.10	–	–	–	–
BERT-PT [78] [79]	–	76.96	84.26	75.08	–	–	81.57	–
BAT [79]	–	76.50	85.57	79.24	–	–	81.50	–
P-SUM [80]	–	79.68	85.94	76.81	–	–	81.99	–
H-SUM [80]	–	79.67	86.09	76.52	–	–	81.34	–
SK-GCN-BERT [81]	–	75.19	–	75.57	–	66.78	–	72.02
SDGCN-BERT [82]	–	76.47	–	78.34	–	–	–	–
RGAT-BERT [39]	–	80.92	–	78.20	–	–	–	–
DGEDT-BERT [105]	–	80.00	–	75.60	–	71.00	–	79.00
DualGCN-BERT [83]	–	81.16	–	78.10	–	–	–	–
BERT-ADA [106]	–	80.05	–	74.09	–	–	–	–
TF-BERT [84]	–	81.15	–	78.46	–	–	–	–
Dual-MRC [107]	–	82.04	–	75.97	–	–	–	–
dotGCN-BERT [85]	–	80.49	–	78.10	–	–	–	–
DPL-BERT [86]	–	84.86	–	78.58	–	–	–	–
SSEGCN-BERT [87]	–	81.09	–	77.96	–	–	–	–
TGCN-BERT [83]	–	79.95	–	77.03	–	82.77	–	72.81
RoBERTa [52]	–	82.10	–	79.73	–	62.41	–	80.88
ASGCN-RoBERTa [89]	–	80.59	–	80.32	–	–	–	–
RGAT-RoBERTa [89]	–	81.29	–	79.95	–	–	–	–
PWCN-RoBERTa [89]	–	80.85	–	81.08	–	–	–	–
SARL-RoBERTa [88]	–	82.44	–	82.97	–	73.83	–	81.92
RoBERTa+MLP [89]	–	80.96	–	80.73	–	–	–	–

MN [108]	–	64.34	–	62.89	–	–	–	–
MN(+AS) [109]	–	69.15	–	65.24	–	–	–	–
TNet [4]	–	71.27	–	71.75	–	–	–	–
TNet-LF [4]	–	71.03	–	70.14	–	59.47	–	70.43
TNet-ATT [109]	–	69.44	–	71.51	–	–	–	–
TNet-AS [4]	–	71.27	–	71.75	–	–	–	–
TNet-ATT(+AS) [109]	–	72.90	–	73.84	–	–	–	–
AE-LSTM [3]	–	64.32	–	62.50	–	–	–	–
ATAE-LSTM [3]	–	64.95	–	62.45	–	–	–	–
TD-LSTM [2]	–	66.73	–	68.43	–	-	–	–
BILSTM-ATT-G [66]	–	70.78	–	69.90	–	–	–	–
LSTM-ATT-CNN [4]	–	68.71	–	68.03	–	–	–	–
LSTM-FC-CNN-LF [4]	–	70.23	–	70.60	–	–	–	–
LSTM+SynATT+TarRep [110]	–	71.32	–	69.23	–	66.05	–	–
LSTM-FC-CNN-AS [4]	–	70.06	–	70.72	–	–	–	–
AEN-BERT [76]	–	73.76	–	76.31	–	–	–	–
AEN-GloVe [76]	–	72.14	–	69.04	–	–	–	–

Literature Review

F1 Scores of Different Models which perform the joint task

Model	Laptop-14	Restaurant-14
InstructABSA [7]	79.34	79.47
GRACE [96]	70.71	77.26
SPAN [112]	68.06	74.92
RACL-BERT [111]	63.40	75.42
BERT-E2E-ABSA [53]	61.12	74.72
DOER [114]	60.35	72.78
IMN [115]	58.37	69.54
E2E-TBSA [113]	57.90	69.80

Second and Third Objectives

- Develop a model that can achieve a high accuracy in recognizing aspects from sentences related to a specific domain within textual reviews

- Build a machine learning model with a high accuracy to identify the polarity of sentences in sentiment analysis

Current Progress

Current Progress

Implemented different approaches to get the most accurate and robust solution.

1. Fine-Tuning LLaMA 2-7B with Quantized Low Rank Adaptation (QLoRA)
2. Fine-Tuning Mistral-7B with Quantized Low Rank Adaptation (QLoRA)
3. SETFIT for efficient few-shot fine-tuning of Sentence Transformers
4. InstructATE-DeBERTaASC (Novel Model)

What is a Large Language Model

A LLM is an **advanced artificial intelligence** designed to **understand** and **generate human-like text** by imposing **massive datasets** and extensive **neural network architectures.**

LLaMA 2 -7B by Meta and **Mistral 7B** by Mistral AI are both 7 billion parameter models designed for general-purpose natural language understanding and generation. Both models are specifically optimized for **high performance** and **efficiency** across various **NLP tasks**.

Fine-Tuning LLMs (LLaMa 2 , Mistral)

1.Parameter Efficient Fine-Tuning (PEFT) with QLoRA on NVIDIA L4 GPU

- **PEFT**
  - Reduce the resources needed for fine-tuning LLMs.
- **QLoRA (Quantized Low-Rank Adaptation)**
  - Uses **decomposed weight matrices** for fewer parameters, maintaining performance with **lower resource demand**

2. Fine-Tuning on Benchmark Datasets and used relevant prompt in the pipeline.

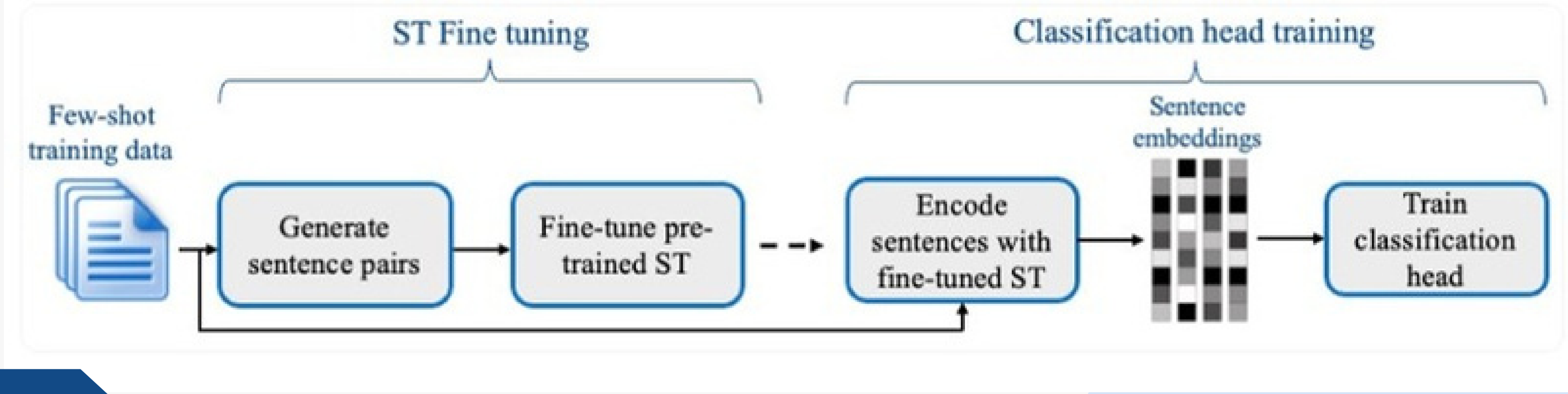
3. Save the fine-tuned models in a model hub separately.

4. Loading and Evaluating Fine-Tuned Models on environment which created in GCP VM.

SetFit

SETFIT(Sentence Transformer Fine-tuning) presents an innovative framework for efficient and prompt-free few-shot fine-tuning of Sentence Transformers (ST).
The SETFIT approach consists of two main steps:

1. Fine-tuning a pretrained ST on a small number of text pairs in a contrastive Siamese manner.
2. Training a classification head using the resulting ST to generate rich text embeddings.



InstructATE-DeBERTaASC

- We developed an aspect-based sentiment analysis pipeline utilizing transformer-based models to automatically extract aspects and analyze sentiments in textual data

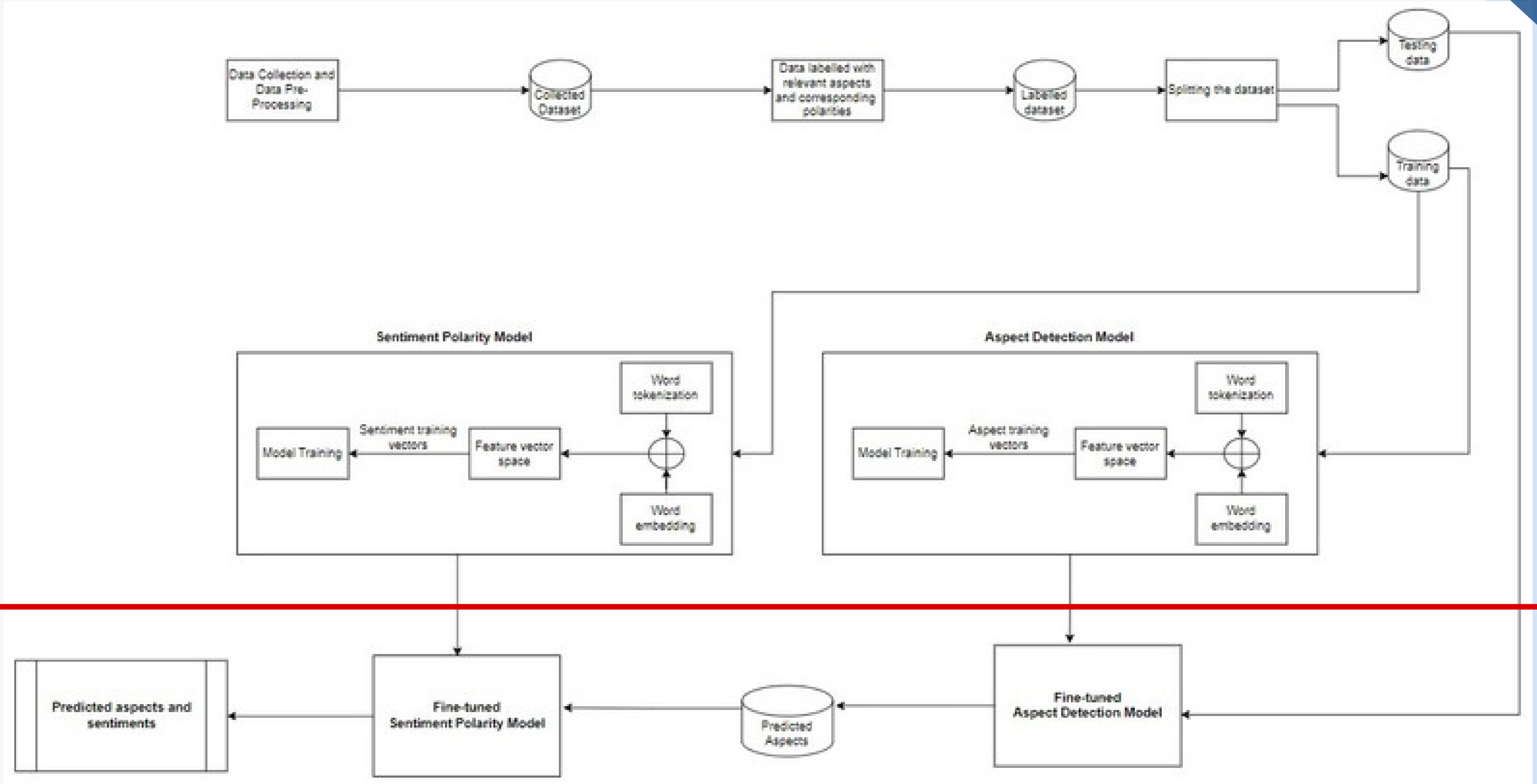
- Our goal was to implement a model that can perform the joint task (ATE + ASC)

- Through our rigorous literature review we identified the best performing models for the single tasks and built our **novel hybrid model**.

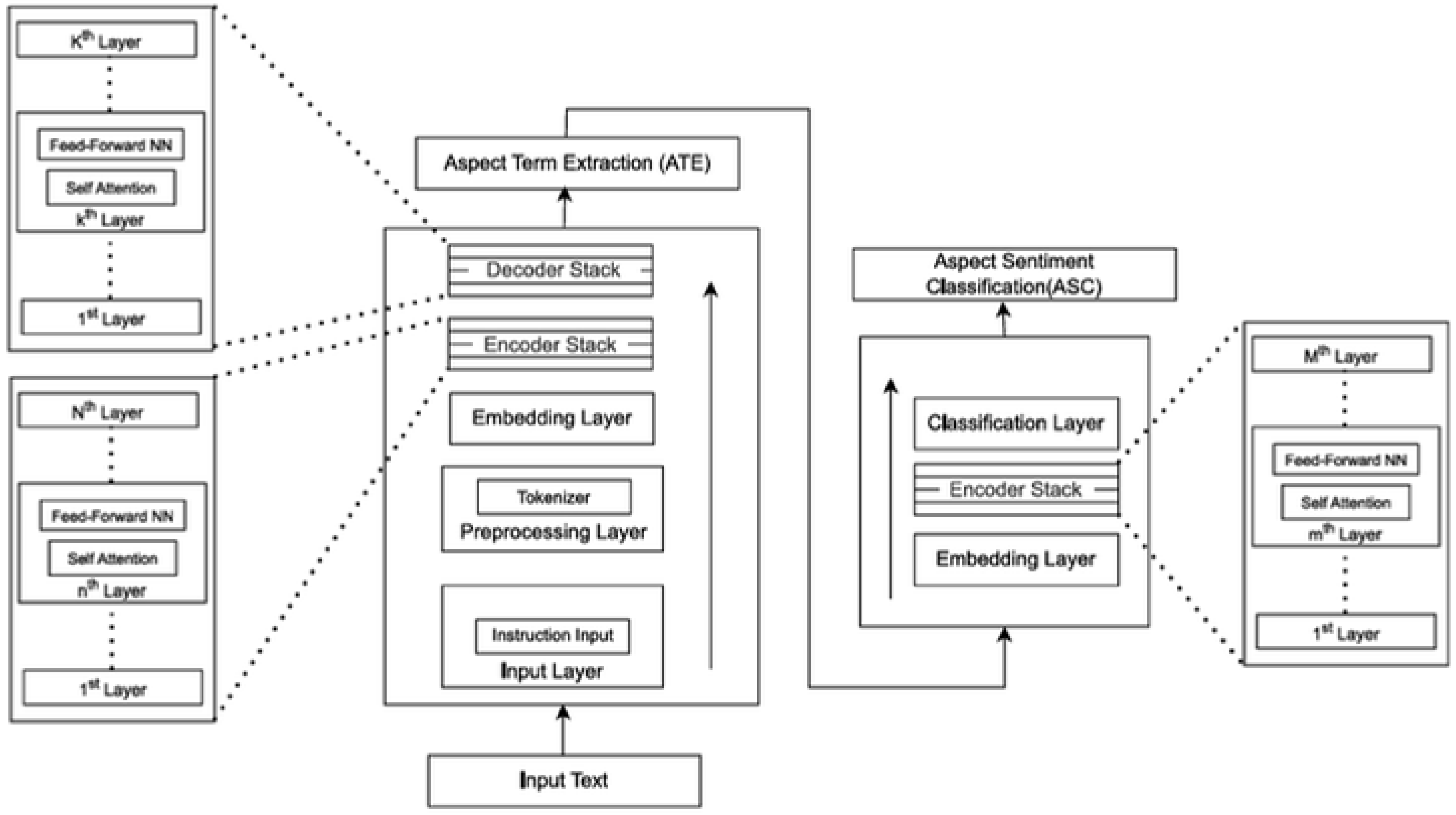
- The sentiment polarity model utilized is **DeBERTa-V3-baseabsa-V1** and the aspect detection model utilized is **InstructABSA.**

- Exploited the strengths of these models to develop our own novel hybrid model named **InstructATE-DeBERTaASC.**

Generalized Novel Model



Layered Architecture of the Novel Model



Model Algorithm

Algorithm 1: Aspect-Based Sentiment Analysis (ABSA)

Require: Review X

Aspect Term Extraction (ATE):

$A_c = f_{ATE}(X)$

Target Aspect Filtering:

$A = f_{filter}(A_c)$

Aspect Sentiment Classification (ASC):

$S = \{\}$

for each aspect term a in A **do**

$s = f_{ASC}(X, a)$

Add (a, s) to S: $S = S \cup \{(a, s)\}$

end for

return Final aspect terms A with sentiment labels S: $\{(a, s) \mid a \in A, s = f_{ASC}(X, a)\}$

Sets:

• X: Review represented as a word sequence (X = {x1, x2, . . . , xn})

• A: Set of extracted aspect terms (A X)

• S: Set of sentiment labels for aspect terms (S {positive, negative, neutral})

Functions:

• f_ATE(X): Function for Aspect Term Extraction. Takes review X and returns candidate terms (Ac). (Ac X)

• f_filter(Ac): A filtering function. Takes candidate terms and returns refined aspects (A). (A Ac)

• f_ASC(X, a): Function for Aspect Sentiment Classification. Takes review X and an aspect term a, returns sentiment labels (S {positive, negative, neutral})

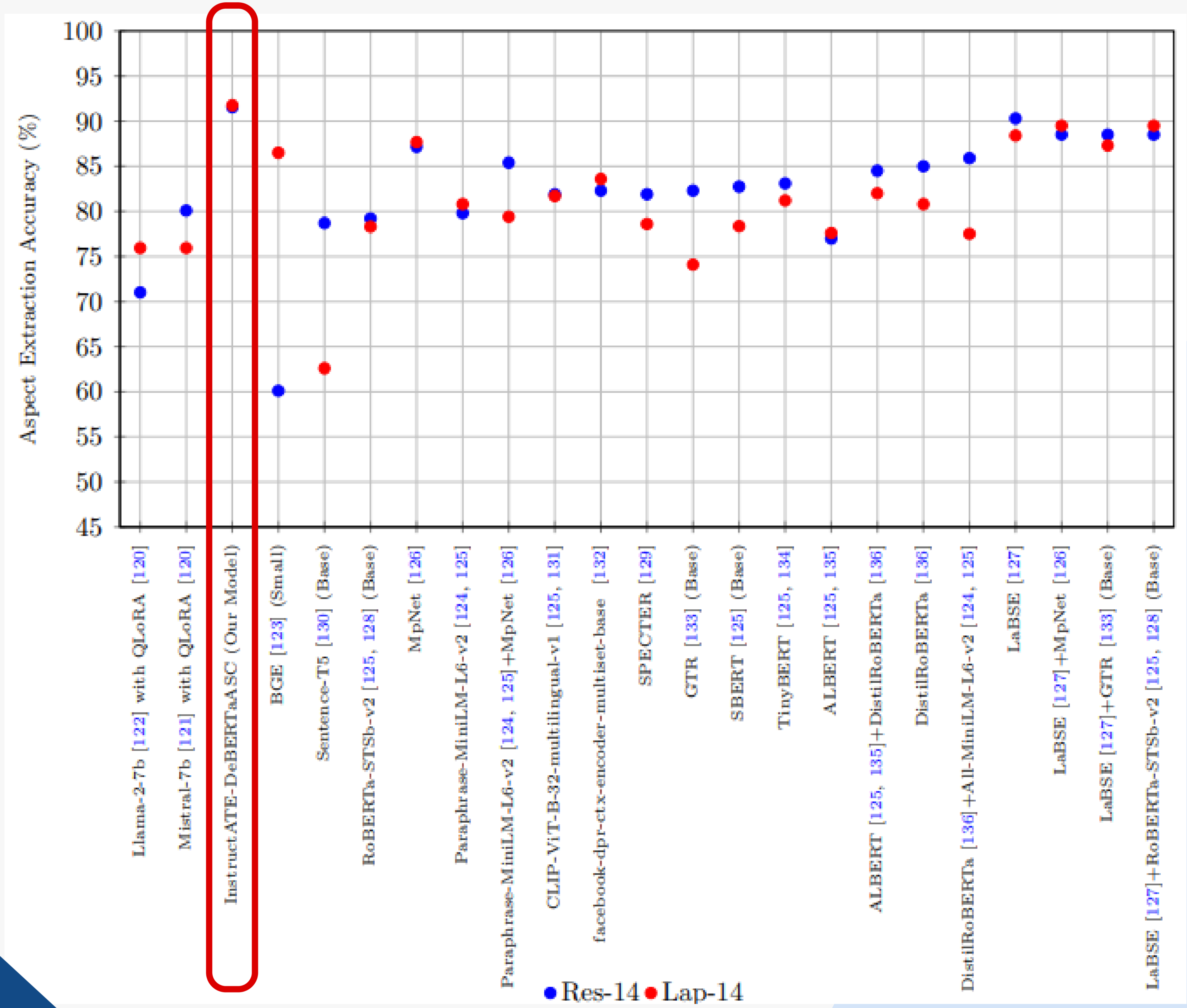
Progress Results

Progress Results

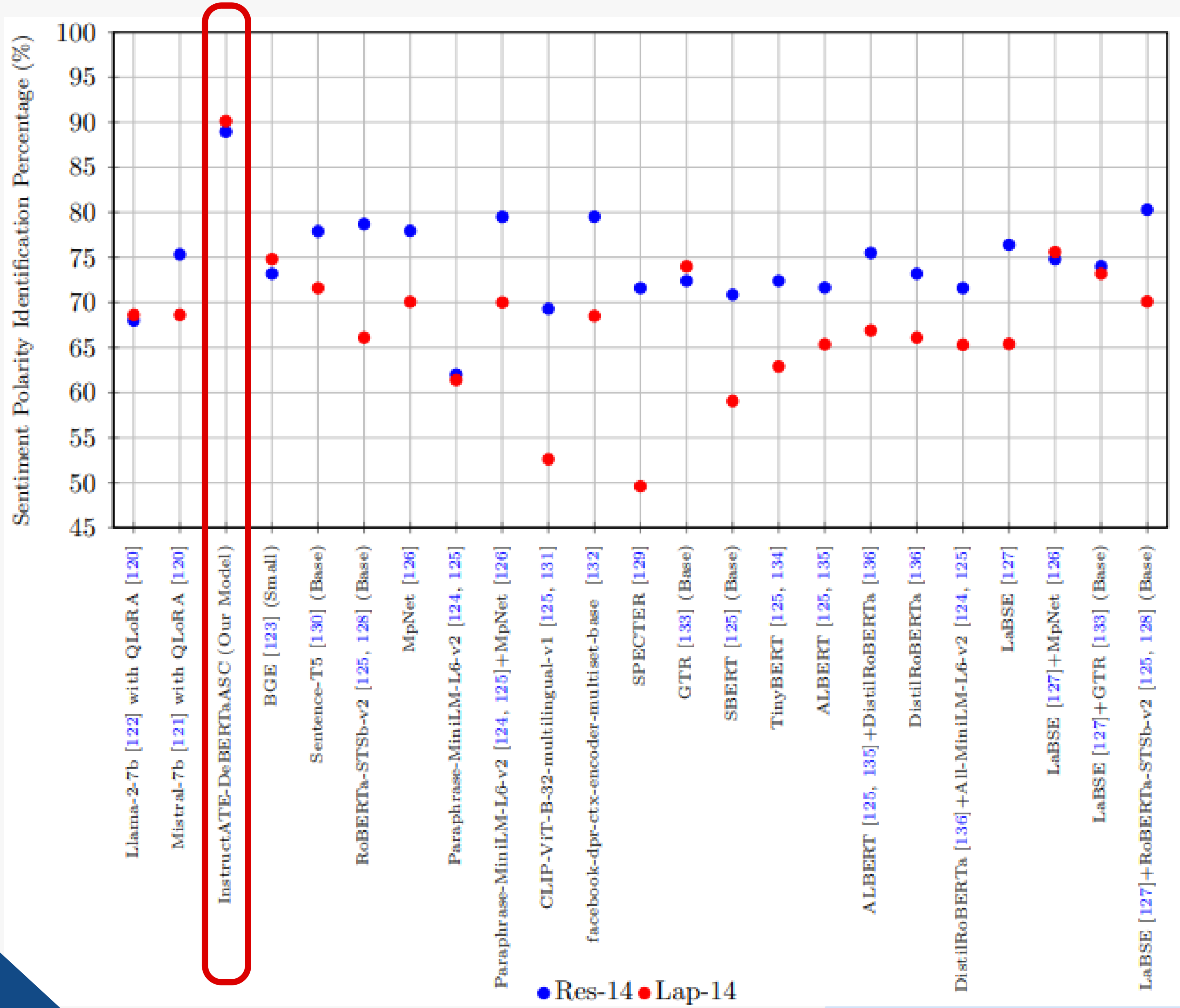
F1 Scores of Joint Task Implemented Models on the SemEval 2014 Benchmark

	Model	F1 Score (%)			
		Res-14		Lap-14	
		Aspect Extraction	Sentiment Polarity	Aspect Extraction	Sentiment Polarity
	Llama-2-7b [122] with QLoRA [120]	71.94	69.29	71.66	66.53
	Mistral-7b [121] with QLoRA [120]	81.33	76.46	77.65	72.40
	InstructATE-DeBERTaASC (Our Model)	**91.39**	**88.63**	**91.56**	**89.65**
SETFIT [8]	BGE [123] (Small)	72.24	75.59	64.79	75.59
	Sentence-T5 [130] (Base)	56.82	78.74	63.29	74.01
	RoBERTa-STSb-v2 [125, 128] (Base)	82.37	77.95	84.26	67.71
	Paraphrase-MiniLM-L6-v2 [124, 125]	84.58	71.65	83.14	64.56
	+MpNet [126]	84.58	78.74	79.40	70.07
	CLIP-ViT-B-32-multilingual-v1 [125, 131]	81.49	59.05	73.03	53.54
	facebook-dpr-ctx-encoder-multiset-base [132]	76.54	78.74	75.52	77.45
	SPECTER [129]	81.93	71.65	77.52	55.11
	GTR [133] (Base)	81.85	74.80	84.70	74.80
	SBERT [125] (Base)	83.18	70.86	84.32	61.41
	TinyBERT [125, 134]	78.76	73.22	82.83	63.77
	ALBERT [125, 135]	80.08	74.80	80.22	66.92
	+DistilRoBERTa [136]	81.49	74.81	79.40	68.50
	DistilRoBERTa [136]	84.95	75.59	80.97	69.29
	+All-MiniLM-L6-v2 [124, 125]	85.46	71.65	81.27	63.77
	MpNet [126]	86.28	77.95	88.80	73.22
	LaBSE [127]	89.38	73.23	90.30	64.57
	+MpNet [126]	88.55	74.80	89.51	75.59
	+GTR [133] (Base)	88.55	74.02	87.27	73.22
	+RoBERTa-STSb-v2 [125, 128] (Base)	90.30	77.17	89.51	70.08

Aspect Extraction Accuracy of Joint Task Implemented Models

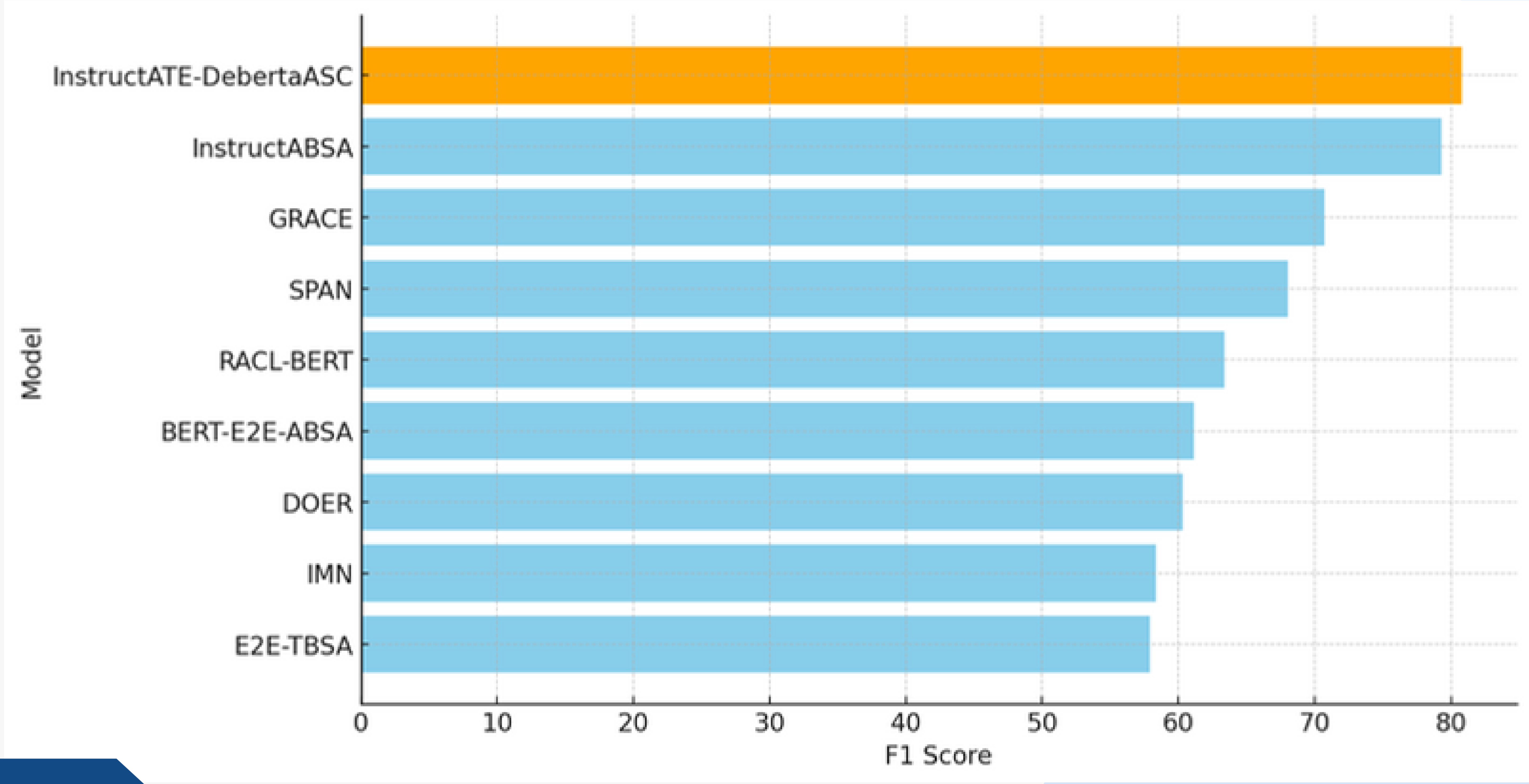


Sentiment Polarity Percentage of Single Task Implemented Models



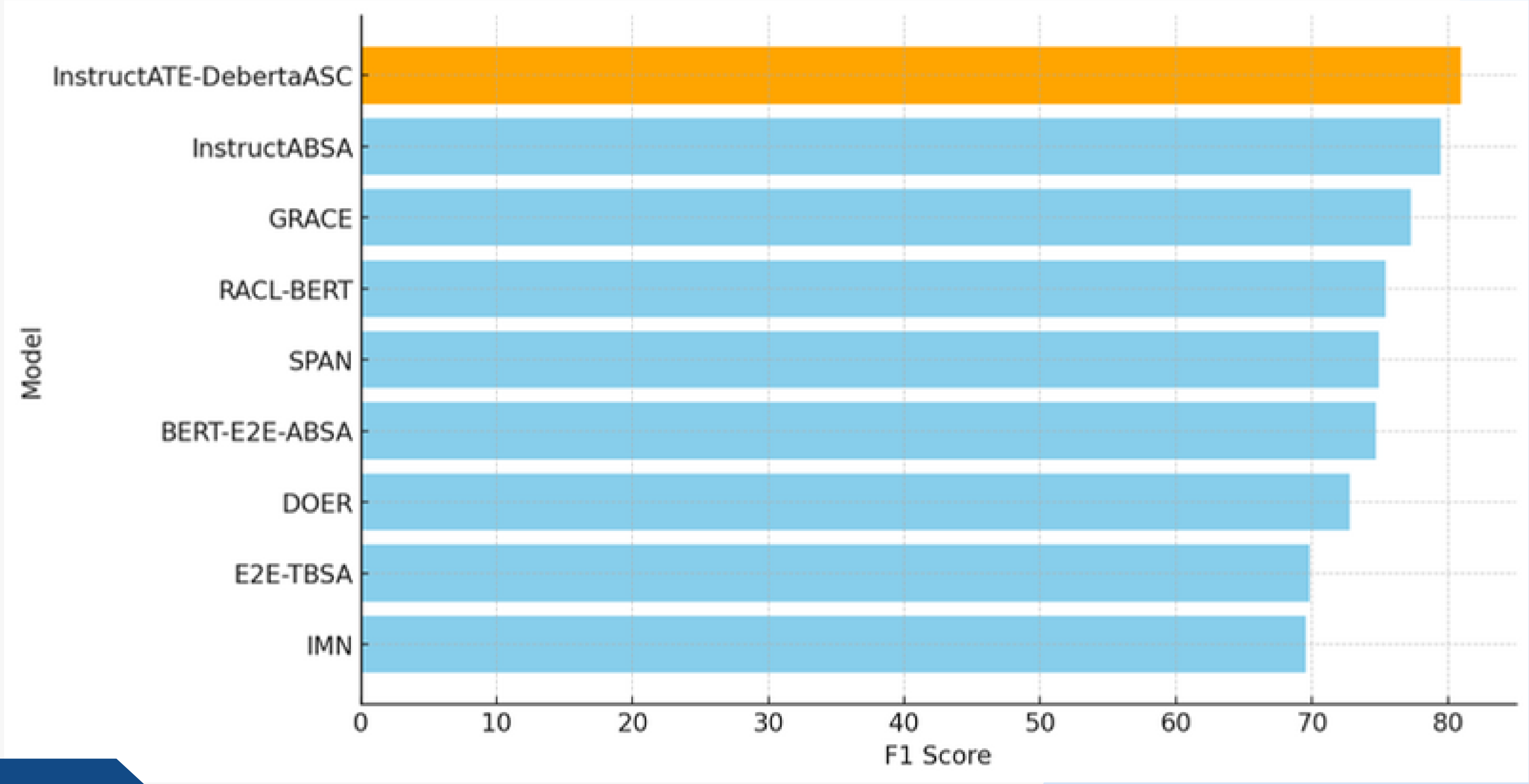
Progress Results

F1 scores of Models for the joint task of ASC and ATE for laptop-14



Progress Results

F1 scores of Models for the joint task of ASC and ATE for restaurant-14



Cost Effectiveness and Benefits for Both Parties

Total Monthly Cost for our proposed model

Approximate Cost of our Project =
+ $26 (Cloud GPU)
+ $20 (Deploy Costs)
+ $6 (Other)
= **$52**
= **LKR 15,500**

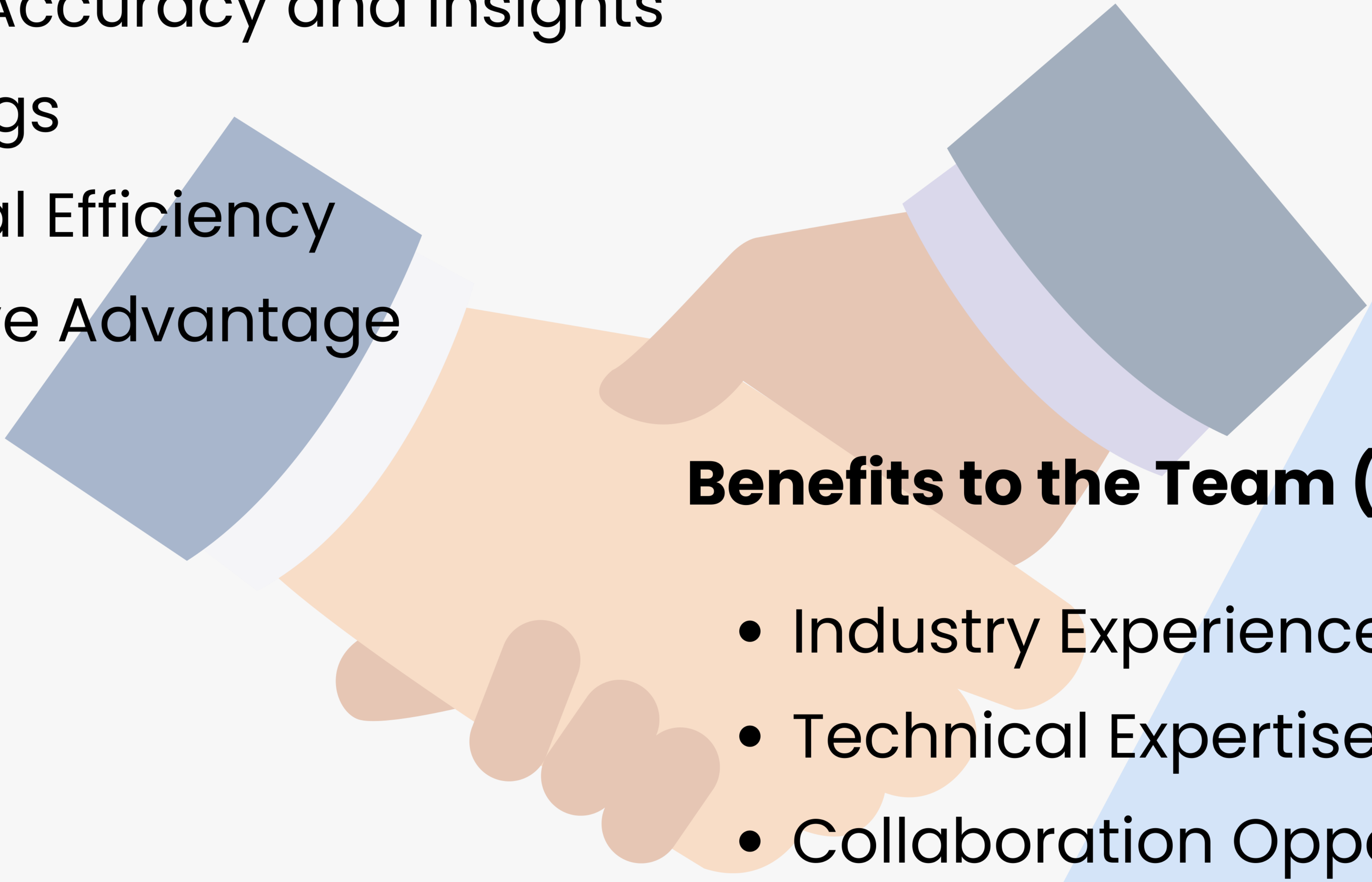
Total Monthly for the company for the current employed system

Total Cost of Company =
+ $3 (Training)
+ $450 (Inference)
+ $0.023 (Storage)
+ $0.00675 (Data Transfer)
= **$453.03**
= **LKR 136,200**

Benefits for both parties

Benefits to Emojot (Pvt) Ltd.

- Improved Accuracy and Insights
- Cost Savings
- Operational Efficiency
- Competitive Advantage

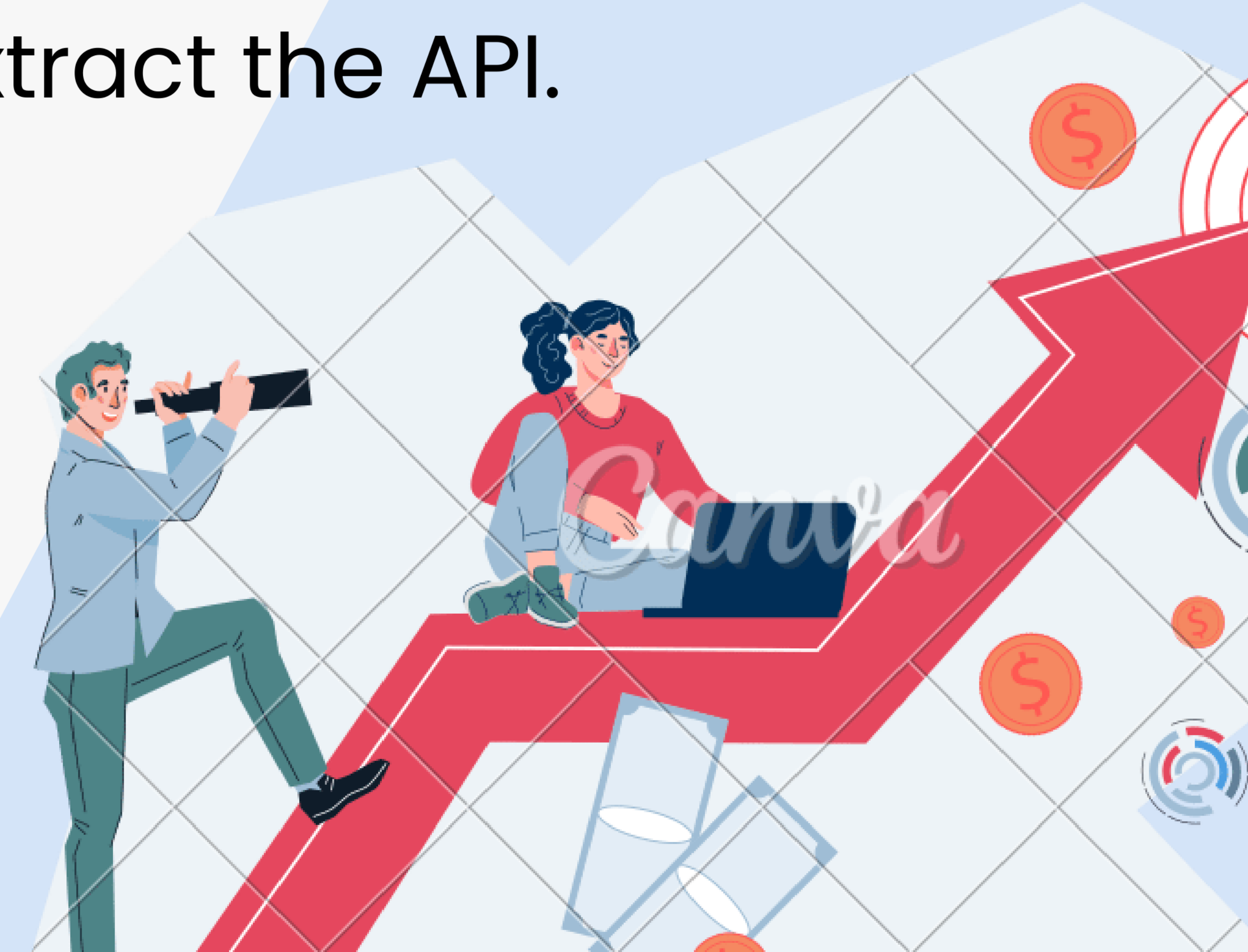


Benefits to the Team (Us)

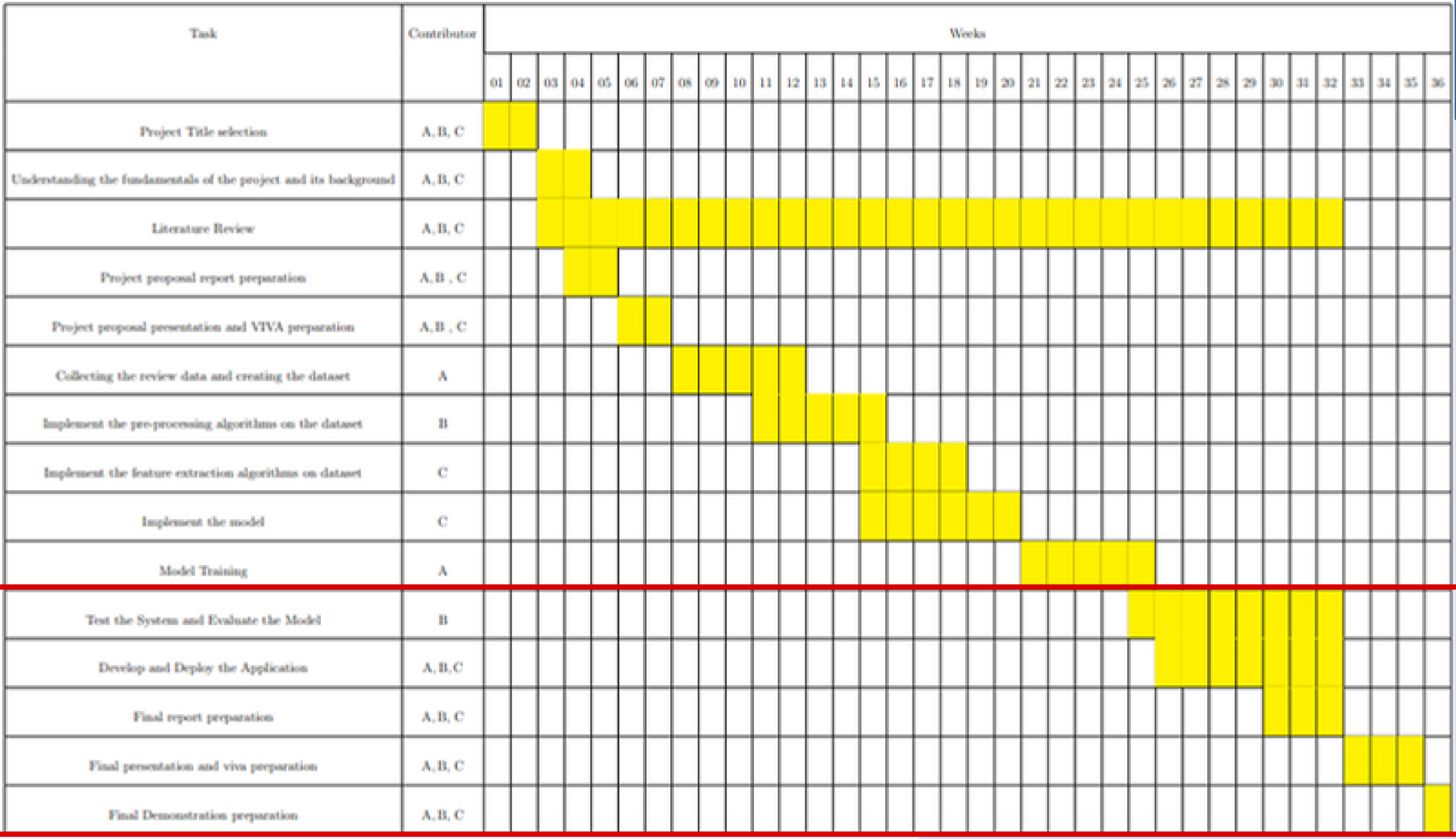
- Industry Experience
- Technical Expertise
- Collaboration Opportunities

Future Works

- Increase the accuracy of the developed novel model further.
- Categorize the aspects according to company requirements
- Develop a user-friendly application.
- Deploy the model in a Cloud Environment and extract the API.
- Extend the research further.
- New implementation for a complete user review experience system



Project Timeline



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Thank You

For Your Attention

Supplementary Slides

For Literature Review
Single Task Models

Detailed Literature Review

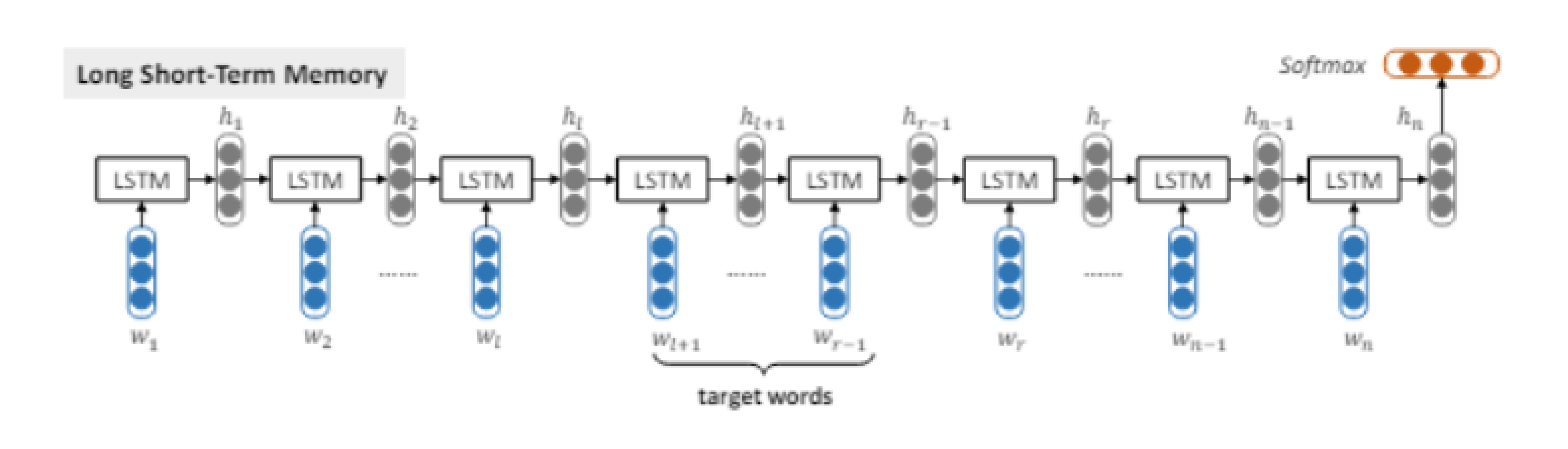
LSTM Based

- Recurrent Neural Networks (RNNs) are an extension of conventional feed-forward neural networks designed to handle sequential data by integrating loops within the network.

- RNNs got problems as, primarily the vanishing gradient and exploding gradient problems.

- In order to overcome these challenges, Long Short-Term Memory (LSTM) network was developed.

Detailed Literature Review



Detailed Literature Review

LSTM Based

- To effectively extract aspect information, Wang et al. proposed a model called **LSTM with Aspect Embedding (AE-LSTM)**
- By learning an embedding vector for each aspect, the AE-LSTM can capture the context and sentiment associated with different aspects within a sentence properly.
- .In the AE-LSTM model, aspect information is included by enabling the aspect embedding which affect the calculation of attention weights

Detailed Literature Review

LSTM Based

- To further leverage aspect information, Wang et al. developed an enhanced model called **Attention-based LSTM with Aspect Embedding (ATAE-LSTM)**

- **Target-Dependent LSTM (TD-LSTM)** model uses two LSTM networks.

- Building on the vanilla LSTM model, a new model named **BILSTM-ATT-G** was developed by Liu and Zhang. This model employs a bidirectional LSTM to represent the input word sequence, enhancing the model's ability to capture dependencies from both directions

Detailed Literature Review

LSTM Based

- Li et al. proposed **Target-Specific Transformation Networks (TNet)**, a new architecture designed to improve target sentiment classification by effectively handling multiple targets and extracting relevant features without introducing noise.

- TNet introduces a novel Target-Specific Transformation (TST) component for generating target-specific word representations. TNet aims to enhance the strengths of both RNNs and CNNs while mitigating their respective limitations.

- To enhance context information, which has been shown to be useful by Lai et al. , two strategies were investigated: Lossless Forwarding (LF) [4] and Adaptive Scaling (AS) .The model variants are named **TNet-LF and TNet-AS.**

Detailed Literature Review

LSTM Based

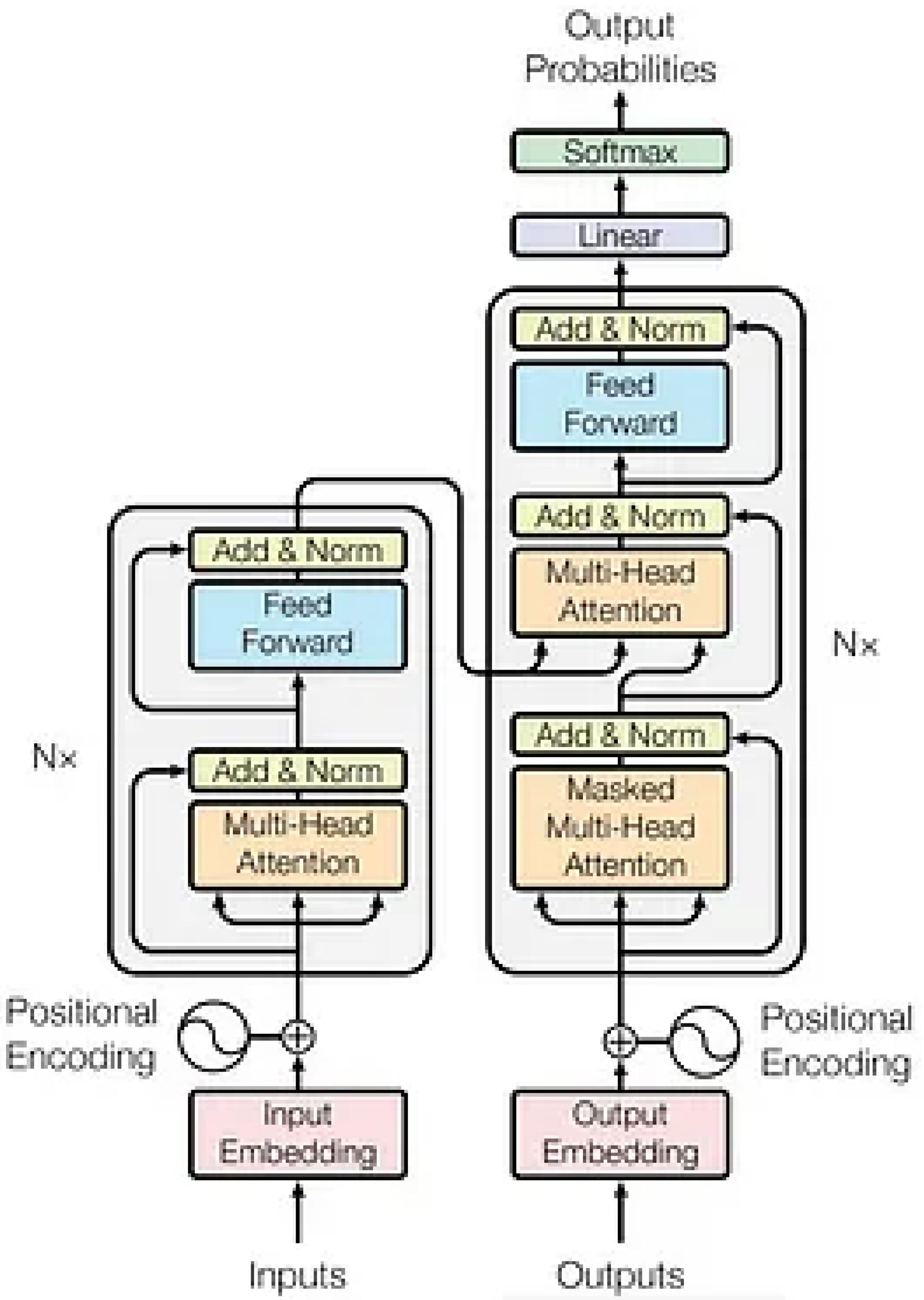
- **LSTM-ATT-CNN** which is mentioned by Li et al. applies attention as an alternative and does not require a context-preserving mechanism, but it performs significantly worse than the TNet variants

- The models **LSTM-FC-CNN-LF** and **LSTM-FC-CNN-AS** are built by Li et al. by applying a fully connected (FC) layer to replace the TST and retaining the context-preserving mechanism

Detailed Literature Review

BERT

Encoder



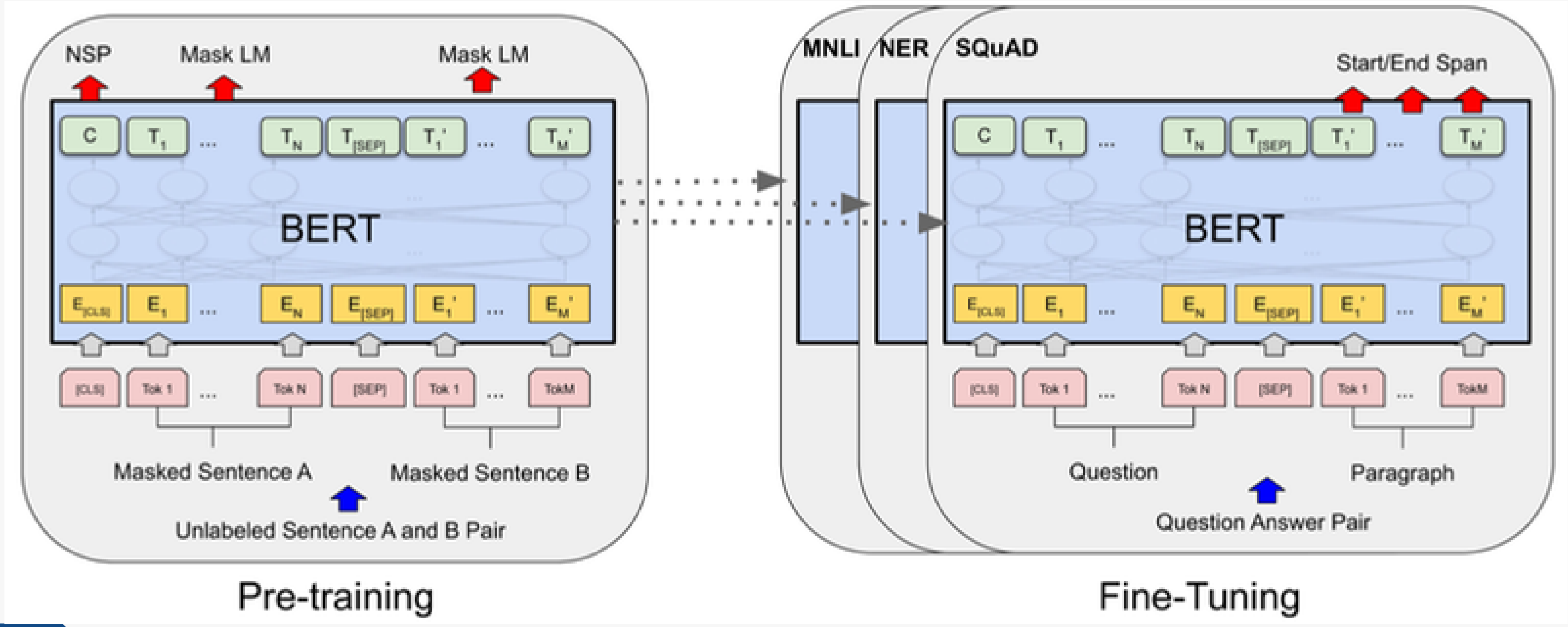
GPT

Decoder

Detailed Literature Review

BERT Based

- **BERT,** which stands for Bidirectional Encoder Representations from Transformers, enhances traditional Transformers by eliminating the unidirectional constraint.



Detailed Literature Review

BERT Based

- BERT’s training process involves two main steps. Pre training and fine tuning.
- During the pre-training phase, BERT is trained on a large corpus of unlabeled text data through various pre-training tasks, including the MLM and next sentence prediction.
- Once pre-trained, BERT is fine-tuned for specific downstream tasks using labeled data. During fine-tuning, all the parameters are adjusted based on the specific requirements of the task.
- Although different tasks use the same pre-trained BERT model as a starting point, each task results in a separately fine-tuned model optimized for that particular application.

Detailed Literature Review

BERT Based

- Researchers have developed enhanced versions of BERT.

- **BERT-DK**, introduced by Zhao, integrates domain-specific knowledge to improve ABSA performance

- **BERT-SPC**, developed by Song et al., employs a Sentence Pair Classification framework to better understand the context of aspect-specific sentences. The sentence pair framework helps in understanding relationships between sentences, thereby improving sentiment classification accuracy.

- Although different tasks use the same pre-trained BERT model as a starting point, each task results in a separately fine-tuned model optimized for that particular application.

Detailed Literature Review

BERT Based

- Innovative approaches such as **BERT-MRC**, proposed by Zhao et al. , frame ABSA tasks as machine reading comprehension problems.

- **BERT-PT** which involves pre-training BERT on domain-specific data followed by fine-tuning.

- **BAT** which stands for **BERT with Adversarial Training**, introduced by Karimi et al., enhances ABSA by generating adversarial examples during training .

- Another approach taken by Karimi et al. utilizes summarization-based approaches to enhance ABSA performance. **P-SUM** and **H-SUM** are such proposed methods.

Detailed Literature Review

BERT Based

- Innovative approaches such as **BERT-MRC**, proposed by Zhao et al. , frame ABSA tasks as machine reading comprehension problems.

- Zhou et al. developed **SK-GCN-BERT** which integrates structural information from sentences and uses graph convolutional networks to capture complex relationships between aspects and sentiments.

- **SDGCN-BERT**, introduced by Zhao et al, combines semantic dependency graphs with BERT. These models use structural and dependency information to enhance their understanding of the text, which eventually improves the performance of ABSA tasks.

Detailed Literature Review

BERT Based

- **RGAT-BERT**, proposed by Bai et al., uses relational graph attention networks to improve aspect extraction and sentiment classification abilities. The use of relational information significantly improves the model's ability to understand and classify relationships within text.

- **DualGCN-BERT** introduced by Li et al., uses dual graph convolutional networks to handle both aspect extraction and sentiment classification. The dual graph approach helps the model to balance and improve both tasks effectively.

- **TF-BERT,** developed by Zhang et al., uses task-specific fine-tuning strategies to improve ABSA performance. Fine-tuning strategies enable the model to adapt better to the complexities of ABSA tasks

Detailed Literature Review

BERT Based

- **DotGCN-BERT,** proposed by Chen et al., uses dot-product based **graph convolutional networks** to improve ABSA performance. By using dot-product operations, this model is able to effectively understand and classify relationships between aspects and sentiments.

- **DPL-BERT** proposed by Zhang et al. has deep prompt learning, which makes the prompt update rapid when new ABSA tasks come through. Prompt learning effectively guides the learning of the model itself to have a sharp focus on one task.

- **SSEGCN-BERT** proposed in Zhang et al. introduces semantically structural embeddings into the BERT pre-trained model.

Detailed Literature Review

RoBERTa Based

- **RoBERTa** (Robustly optimized BERT approach) is an advanced language model that builds upon the foundational work of BERT.

- The authors of RoBERTa carefully examined the effects of important hyperparameters and training data size through a replication study of BERT pretraining, and they found that BERT was significantly undertrained.

- RoBERTa’s development involved several critical modifications to BERT’s original design: **training the model for a longer period with larger batch sizes** and **over more data**, **removing the next sentence prediction objective** which was part of BERT’s original training regimen, **training on longer sequences to better capture context**, and **employing a dynamically changing masking pattern applied to the training data.**

Detailed Literature Review

RoBERTa Based

- **SARL-RoBERTa** model, which was introduced by Wang et al., uses span-based dependency modeling to align opinion candidates with aspects and uses an adversarial learning strategy to reduce sentiment bias in aspect embeddings.

- Strong performance is achieved by the **ASGCN-RoBERTa** model, which combines an aspect-specific graph convolutional network with dependency tree syntactic information.

- With a relational graph attention network integrated to collect relational information between words, **RGAT-RoBERTa** performs admirably.

- **RoBERTa+MLP** integrates a multi-layer perceptron with RoBERTa, it highlights the flexibility of combining RoBERTa's embeddings with simple classifiers.

Detailed Literature Review

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Detailed Literature Review

RoBERTa Based

- **PWCN-RoBERTa** combines a position-weighted convolutional network with RoBERTa to emphasize positional information.

Detailed Literature Review

DeBERTa Based

- **DeBERTa (Decoding-enhanced BERT with disentangled attention)** presents a significant advancement in the field of natural language processing by enhancing the attention mechanisms used in earlier models like BERT and RoBERTa.

- DeBERTa introduces a disentangled attention mechanism. Unlike BERT, where each word is represented by a single vector that combines content and positional embeddings, DeBERTa utilizes two separate vectors for each word to represent its content and position independently.

- While traditional MLM tasks predict masked words based only on the surrounding context, DeBERTa improves this by using absolute positional information along with the con-textual embeddings of word contents and positions before the softmax layer

Detailed Literature Review

DeBERTa Based

- Further, DeBERTa during fine-tuning also uses virtual adversarial training, which is a procedure to boost the generalization power over a wide variety of linguistic tasks through perturbing the input data with small perturbations and retraining the model against those perturbations.

- Improving from the vanilla DeBERTa model a new model named **DeBERTaV3** by He et al. It improves the original DeBERTa model by replacing masked language modeling (MLM) with replaced token detection (RTD), a more sample-efficient pre-training task.

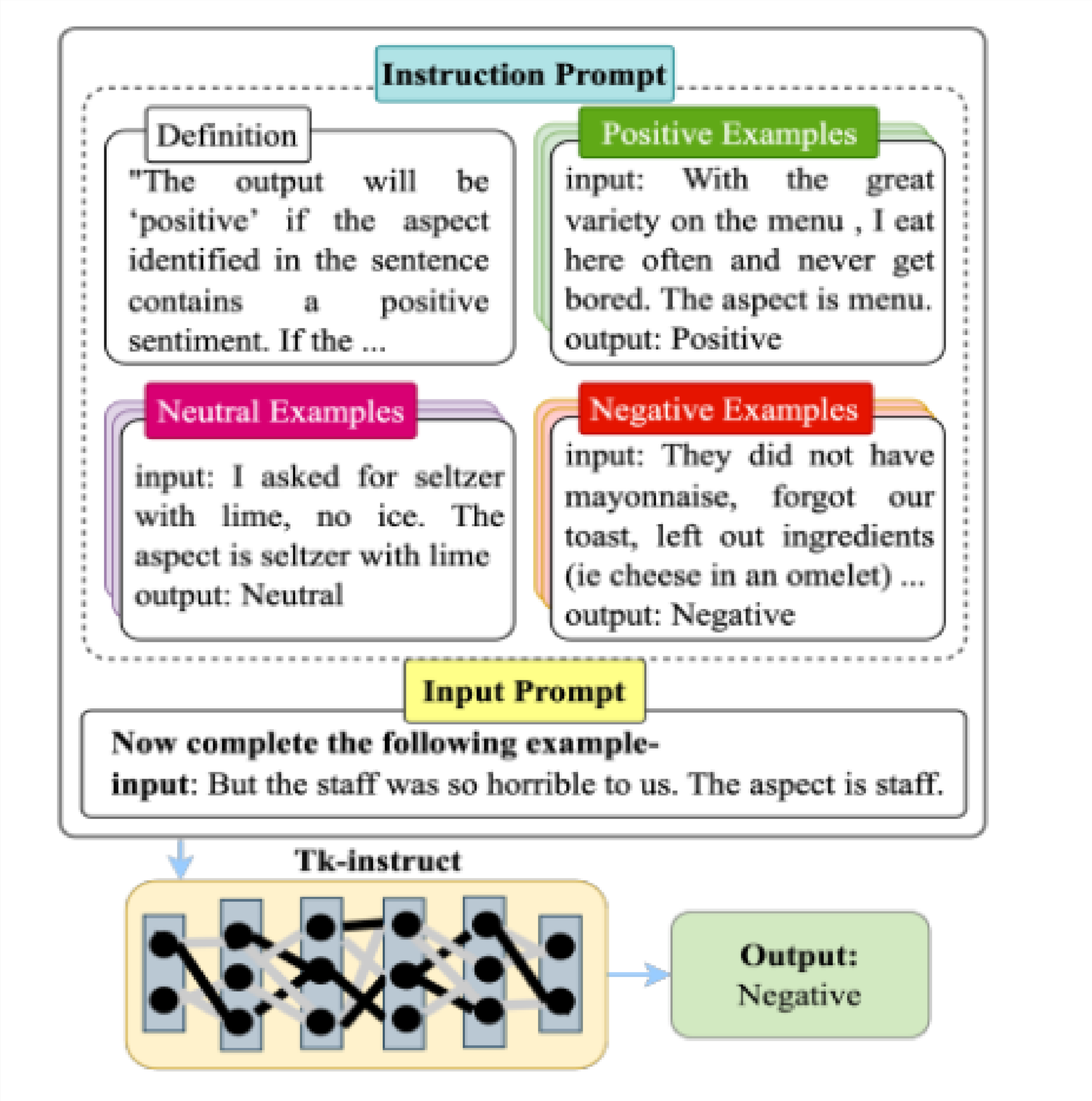
- Neighbouring aspects usually share similar sentiments, which is known as "aspect sentiment coherency." To address this, they proposed a local sentiment aggregation paradigm (LSA) to effectively model fine-grained sentiment coherency. In respect to that, the **LSA-X-DeBERTa** model was introduced.

Detailed Literature Review

Other Models

- **LCF-ATEPC-CDM**, employs a Local Context Focus technique and performs well.

- **InstructABSA , based on T5**



Detailed Literature Review

Other Models

- **BART-ABSA** model in a comprehensive approach to ABSA has also been demonstrated by Yan et al. , which combines all ABSA subtasks into a single generative formulation**.**

- BART is a transformer-based machine learning model that combines both bidirectional and autoregressive techniques. It's primarily designed for sequence-to-sequence tasks and has been pretrained on a large corpus of text data. BART is unique in that it is trained by corrupting text with an arbitrary noising function and learning to reconstruct the original text. This pretraining helps it understand context, grammar, and the nuances of language effectively.

- **RAM,** leveraging multiple attention mechanisms, showed lower performance in sentiment polarity classification, suggesting that while attention mechanisms can capture long-range dependencies, they might not be as effective in sentiment polarity classification compared to other models

Detailed Literature Review

Other Models

- **ASCNN and ASGCN**, proposed by Zhang et al., integrate attention mechanisms and graph convolutional networks to address syntactical constraints and long-range dependencies, showing moderate performance in sentiment polarity classification

- **MCRF-SA**, presented by Xu et al., employs multiple CRFs (Conditional Random Fields)-based structured attention to capture variable-length opinion spans effectively.

- **KaGRMN-DSG**, introduced by Xing and Tsang, combines local syntactic and global relational information to enhance aspect sentiment classification, addressing challenges in aspect representation.

Detailed Literature Review

Other Models

- **MGAN,** proposed by Li et al., utilizes multiple attention networks to differentiate between aspects, showing competitive performance in aspect sentiment classification.

- **PRET+MULT** focuses on transferring knowledge from document-level data, while **MemNet** explicitly captures the importance of each context word for sentiment polarity.

- **IAN,** proposed by Ma et al., uses interactive attention networks to separately model targets and their contexts, demonstrating effectiveness in aspect sentiment classification.

For Literature Review
Joint Task Models

Detailed Literature Review

- **GRACE,** which was proposed by Luo et al. and addresses the imbalance issue in aspect term extraction, obtained reasonable performance in aspect extraction.
- Through a combination of multitasking and relation propagation, **RACL-BERT** considers the connections between these elements, leading to more accurate sentiment analysis.
- **SPAN** introduced by Hu et al. uses another novel approach. Instead of tagging each word in a sentence, it focuses on picking out key opinion points directly.
- **E2E-TBSA** which stands for End-to-End Target Aspect-Based Sentiment Analysis, is a model proposed by Li et al. in 2019 to address two tasks at once: ATE and ASC.

Detailed Literature Review

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- **E2E-TBSA** which stands for End-to-End Target Aspect-Based Sentiment Analysis, is a model proposed by Li et al. in 2019 to address two tasks at once: ATE and ASC. Here the model uses a collapsed approach where the model combines ATE and ASC into a single, unified task. The model learns the relationship between identifying aspects and their sentiment simultaneously

Detailed Literature Review

- **BERT-E2E-ABSA** introduced by Li et al. relies on the same concepts as E2E-TBSA and is purely based on BERT models

- **DOER** introduced by Luo et al. uses a cross-shared RNN framework to generate all aspect term-polarity pairs of the input sentence simultaneously.

- **IMN** which was introduced by He et al. uses an interactive architecture with multi-task learning for end-to-end ABSA tasks. It contains aspect term and opinion term extraction besides aspect-level sentiment classification

Our Models

SETFIT Models

- The **BGE** (small) model is a variant of the **Bilingual Google Embeddings** model, optimized for efficiency and reduced computational resources while still providing effective bilingual word embeddings.

- Google/**sentence-t5** (Text-To-Text Transfer Transformer) family of models encode text into high-dimensional vectors that can be used for text classification, semantic similarity, clustering.

- **MPNet** (Masked and Permuted Network) is a transformer-based model introduced by Microsoft. It combines the strengths of Masked Language Modeling (MLM) and Permuted Language Modeling (PLM) to capture both local and global context, leading to better performance in understanding the relationships between words and the overall meaning of sentences.

SETFIT Models

- **SBERT** (Sentence-BERT) is an adaptation of BERT designed to generate efficient and high-quality sentence embeddings. It modifies BERT by adding a pooling layer to produce fixed-size sentence vectors.

- **TinyBERT** is a distillation-based model designed to create a smaller, faster version of BERT while preserving much of its performance, and less layers.
- **ALBERT** (A Lite BERT) is a variant of BERT.

- **SPECTER** (Scalable Embedding for Content-Based Retrieval) is a neural network architecture designed for generating document embeddings.

- **clip-ViT-B-32-multilingual-v1** is a multi-lingual version of the OpenAI CLIP-ViT-B32 model. (VT: Vision Transformer, CLIP: Contrastive Language-Image Pre-training)

SETFIT Models

- **LaBSE** (language-agnostic BERT sentence embedding) encodes text into high dimensional vectors.

- **GTR** (Generalizable T5-based dense Retrievers) models are dual encoders that encode two pieces of text into two dense vectors respectively. This is typically used to encode a query and a document to compute their similarity for dense retrieval.

- **MiniLM** (Miniature Language Model) is a family of small and efficient transformer models.

- **facebook-dpr-ctx_encoder-multiset-base** model is based on the Facebook DPR (Dense Passage Retrieval) framework, specifically using the context encoder component.

STSB stands for the "**Semantic Textual Similarity Benchmark**."

Layered Architecture

Layered Architecture

Inside ATE Model

- **Instruction Input-** instructions or queries regarding the aspect extraction.
- **Tokenization -**The input text and instruction are tokenized into sequences of tokens.
- **Embedding Layer-** Converts tokens into dense vectors (embeddings).
- **Encoder Stack-** Processes the input sequence to generate contextualized embeddings.
- **Decoder Stack-** Generates the output sequence with identified aspects.

Layered Architecture

Inside Encoder and Decoder Stack

- **Self-Attention Mechanism-** This mechanism allows the model to focus on different parts of the input text to capture relationships between words, regardless of their position in the sequence. It helps the model understand the context in which each word appears.
- **Feed-Forward Neural Network-** After the self-attention mechanism, the output is passed through a feed-forward neural network, which applies additional transformations to the data.

Layered Architecture

Inside ASC model

- **DeBERTa Encoder Stack-** Processes the input sequence to generate contextualized embeddings for sentiment classification.
- **Classification Layer-** Assigns sentiment labels (positive, negative, neutral) to each aspect term.

What is a GCP


Cost Effective
Highly Scalable
Custom Machine Types
Internet of Things
Google Cloud Platform
Serverless
Cloud AI
Big Data Analytics
API Platform and Ecosystem
IoT

Fine-Tunning LLM

Fine-Tuning on Benchmark Datasets

- Fine-tuned on **SemEval 14 Laptop** and **Restaurant** data sets
- **Configure parameters** (learning rate, batch size, epochs).
- **Save** fine-tuned models separately in to open-source hubs

Loading and Evaluating Fine-Tuned Models

- **Load** the saved models execute on prepare environment in GCP VM .
- Evaluate on SemEval 14 test data sets