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Enhanced Large Language Models

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Abstract: This work studies ways for improving the effectiveness of a language model in creating and understanding dialogue summaries. Two primary approaches are investigated, in the Complete Fine-Tuning step, a pre-trained FLAN-T5 model is fine-tuned using a dataset of dialog-summary pairs. The dataset is pre-processed to provide explicit instructions to the model, and the fine-tuning process involves training the entire model on the dataset. Qualitative and quantitative evaluations are then conducted to assess the effectiveness of the fine-tuned model in generating summaries. In the PEFT phase, a more computationally efficient method is employed, utilizing Low-Rank Adaptation (LoRA) to train a new layer/parameter adapter while keeping the underlying FLAN-T5 model frozen. This approach significantly reduces computational resources compared to Complete Fine-Tuning while maintaining comparable performance. The resulting model, equipped with the PEFT adapter, is evaluated qualitatively and quantitatively to measure its summarization capabilities. Both approaches sheds light on the compromises between computing efficiency and model performance.

Keywords: Fine tuning, Parameter-efficient fine-tuning (PEFT), ROUGE metric evaluation.

1. INTRODUCTION

The ability to distill vast amounts of text into succinct and coherent summaries holds immense value across a multitude of applications. Among the myriad tasks within NLP, dialogue summarization stands out as a particularly challenging yet crucial endeavor. Dialogue summarization involves condensing conversational exchanges between multiple parties into concise summaries, retaining essential information while discarding redundant or extraneous details.

In this study, a thorough investigation of dialogue summarization techniques is conducted, with a focus on using advanced pre-trained LMs to improve summary accuracy and efficiency. Specifically, two different methodologies are viewed, both of which aim to improve the performance of language models for dialogue summarization.

The Complete Fine-Tuning approach entails a meticulous process of training the entire language model on a curated dataset comprising dialog-summary pairs. This involves preprocessing the dataset to prepare the dialogues and corresponding summaries for input into the model. By this process the model on the entirety of the dataset, it is enabled to learn task-specific nuances and patterns directly from the data. The potential benefits of this approach include improved summarization quality and adaptability to diverse dialogue structures and topics. In contrast, the PEFT methodology offers a more streamlined and resource-efficient alternative to full fine-tuning. Drawing inspiration from the concept of Low-Rank Adaptation (LoRA), PEFT involves training a new layer or parameter adapter while keeping the underlying language model frozen. This approach significantly reduces computational overhead, making it feasible to train on resource-constrained environments or scale up to larger datasets without sacrificing summarization quality.

Throughout the investigation, a thorough evaluation of both approaches are conducted, employing a combination of qualitative and quantitative metrics to assess their efficacy in generating accurate and coherent dialogue summaries. By comparing the effectiveness of the complete fine-tuned model against the PEFT-adapted model, it is aimed to elucidate the trade-offs between computational efficiency and summarization quality, providing valuable insights for practitioners and researchers in the field of NLP. The study contributes to advancing the frontier of dialogue summarization techniques, paving the way for the creation of more advanced NLP systems that are able to extracting key insights from conversational data across various domains and applications.

Evaluate the performance of fine-tuning approaches and investigate the influence of various training paradigms on dialogue summarization quality. We examine the efficacy of multiple fine-tuning approaches in fine-tuning language models for the summarization job. Zero-shot learning includes using a pre-trained model to create summaries without any task-specific fine-tuning. One-shot learning includes fine-tuning the model on one instance or prompt, whereas few-shot learning requires training the model on just a handful of examples. By analyzing the models' performance across these many learning settings, we obtain insight into the robustness and adaptability of the fine-tuned models to variable training data volumes.

The study delves into the qualitative aspects of dialogue summarization, assessing the coherence, relevance, and informativeness of the generated summaries. Through human evaluation and analysis, we seek to understand how well the fine-tuned models capture the essence of the dialogues while maintaining readability and fluency. Furthermore, we investigate the possibilities for using generation of advanced natural language approaches, which include controlled text production and semantic comprehension, to improve the quality of dialogue summaries.

The research extends beyond the performance evaluation of individual models to explore the broader implications and applications of dialogue summarization in real-world scenarios. By examining use cases across domains such as customer support, healthcare, and education, we highlight the practical utility of dialogue summarization in facilitating information retrieval, decision-making, and knowledge dissemination. We also discuss the challenges and limitations inherent in current dialogue summarization techniques, such as handling multi-party conversations, preserving speaker intent, and addressing biases in summarization outputs. Overall, our findings give helpful perspectives and directions for further study in the subject of dialogue summarization, with the goal of pushing the envelope and enabling the development of more intelligent and efficient natural language processing systems.

2. RELATED WORK

Traditional approaches often relied on rule-based methods or extractive summarization techniques, which select important sentences or phrases from the dialogue to create summaries. More recently, neural network-based methods, such as sequence-to-sequence models, have emerged as powerful tools for abstractive dialogue summarization, creating succinct summaries that convey the main elements of the talk. Furthermore, research into processed LMs for certain uses has yielded encouraging outcomes in terms of summarization quality and efficiency. However, parameter-efficient fine-tuning approaches, such as Low-Rank Adaptation (LoRA), have also gained traction for their ability to achieve comparable performance with reduced computational requirements. This paper builds upon existing literature by investigating the effectiveness of both fine-tuning and parameter-efficient fine-tuning methodologies for dialogue summarization tasks, providing insights into their respective advantages and limitations.

Attention-based architectures such as BERT have transformed natural language processing (NLP), allowing for bidirectional context understanding and subsequent advancements in the field [1]. Dialo GPT, trained on Reddit comment interactions from 2005 to 2017, excels at producing human-like text responses [2]. Span BERT improves on BERT by masking contiguous spans of text and predicting their content, hence improving contextual representation [3].

Empirical research has shown that entity references and text-based context have a considerable influence on Relation Extraction models [4]. Self-supervised learning lowers the comparably high few-shot meta classifier error rate by 4% to 27% on small datasets [5].

This computational framework emphasizes Smoothness-Inducing Regularization as a key component. By imposing smoothness constraints on parameter space, it mitigates overfitting and improves generalization across diverse linguistic patterns [6]. Exploring self-training as a means to enhance unsupervised pre-training for natural language understanding, the text introduces SentAugment, a novel data augmentation technique. SentAugment operates by generating query embeddings tailored to a specific task derived from annotated data., which are then utilized to retrieve relevant sentences, thereby improving the pre-training process [7].

Tackling the constraints of cross-entropy loss in refining natural language understanding models, an innovative approach named Supervised Contrastive Learning (SCL) is presented. SCL strives to enhance generalization by utilizing contrastive learning principles to identify similarities among examples within identical classes [8]. Supervised Contrastive Learning (SCL) improves generalization by capturing similarities between examples within the same class using contrastive learning principles [9].

The "Coke" framework dynamically incorporates contextually pertinent data from knowledge graphs to enhance pre-trained LMs [10].

3. METHODOLOGY

The methodology employed in this study revolves around two key approaches for enhancing dialogue summarization. Each approach involves distinct strategies for training pre-existing language models to specialize in the task of summarizing conversational dialogues. Figure 1 outlines the general methodology followed for both approaches. Fine-tuning entails training a pre-trained LM, specifically the FLAN-T5 model, on dialogue summarization data. This process involves preprocessing the dataset, tokenizing the dialogue-summary pairs, and training the model on the preprocessed data. Additionally, parameter-efficient fine-tuning, specifically Low-Rank Adaptation (LoRA), is explored as an alternative approach. LoRA involves adding adapter layers to the original language model and training only these adapters while keeping the base model frozen. Both fine-tuning and PEFT methods are evaluated qualitatively and quantitatively using metrics such as ROUGE scores to assess the effectiveness of the trained models in generating accurate and concise summaries of dialogues. The qualitative assessment involves human evaluation of the generated summaries to gauge their coherence and informativeness. The quantitative evaluation, on the other hand, leverages metrics such as ROUGE scores to provide objective measures of summarization quality.

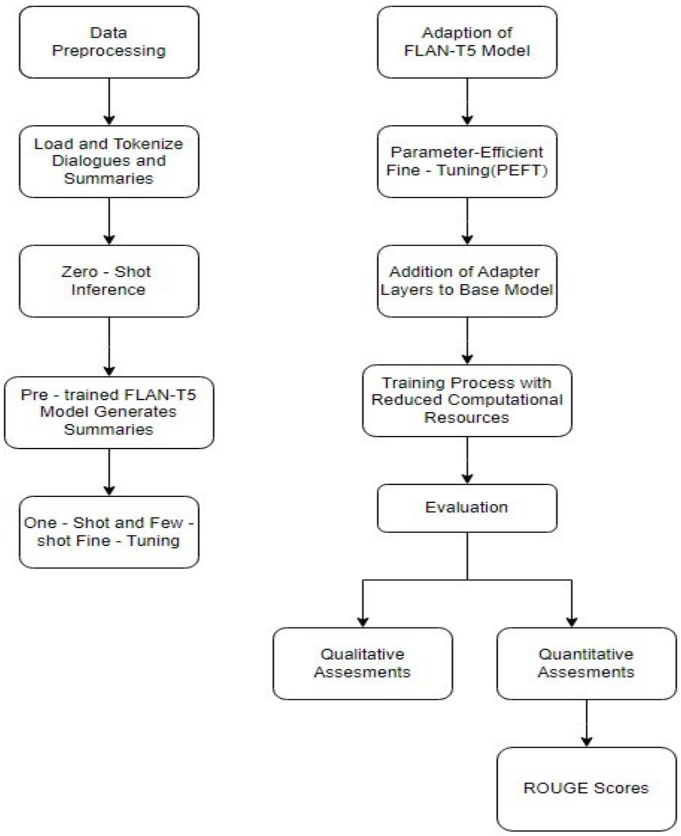

Figure 1. Architecture Diagram

In the above figure 1, the proposed methodology is depicted, detailing the process of dialogue summarization utilizing zero-shot, one-shot, and few-shot fine-tuning approaches. The methodology begins with data preprocessing, involving the loading and tokenization of dialogues and summaries from the DialogSum dataset. Subsequently, the zero-shot inference process is illustrated, showcasing the generation of summaries by the pre-trained FLAN-T5 model without task-specific fine-tuning. Moving forward, the one-shot and few-shot fine-tuning phases are outlined, demonstrating the adaptation of the FLAN-T5 model to the dialogue summarization task with limited training data. Special emphasis is placed on parameter-efficient fine-tuning (PEFT), which involves adding adapter layers to the base model and training with reduced computational resources. Finally, the evaluation phase is presented, incorporating qualitative and quantitative assessments using metrics such as ROUGE scores across all scenarios, ensuring a comprehensive evaluation of the dialogue summarization models.

The process begins with the selection of a pre-trained LM, such as FLAN-T5, which serves as the foundation for the summarization task. The process involves loading a dataset containing dialog-summary pairs and preprocessing it to format the input dialogues and corresponding summaries for training. The dataset is then tokenized and split into 3 different sets.

The fine-tuning procedure begins by initializing the pre-trained LM with certain hyperparameters such as training rate, number of trainings, and size of the batch. The model is trained while monitoring performance on the validation set to prevent overfitting. During training, the model's parameters are adjusted iteratively through backpropagation, optimizing its ability to generate accurate summaries from input dialogues.

Once training is finished, the modified model is assessed on the test dataset using both qualitative and quantitative metrics to assess its summarization quality and effectiveness. This evaluation provides insights into the model's performance and guides further refinements or iterations of the fine-tuning process.

PEFT represents a more resource-efficient alternative to full fine-tuning, designed to minimize computational overhead while maintaining summarization quality. The PEFT methodology leverages techniques such as Low-Rank Adaptation (LoRA) to train lightweight parameter adapters on top of a frozen pre-trained LM.

In the PEFT process, a pre-trained LM, such as FLAN-T5, is augmented with additional adapter layers specifically tailored for the dialogue summarization task. These adapter layers are initialized with low-rank parameterization, lowering the number of variables that can be trained and the difficulty of computation. During training, the underlying language model remains frozen, while only the adapter layers are fine-tuned on the task-specific dataset. This focused training enables the model to learn task-specific features and nuances while preserving the knowledge encoded in the original pre-trained model.

After training the adapter layers, the PEFT-adapted model is evaluated on the test dataset to assess its summarization performance. Comparisons with the full fine-tuned model provide insights into the trade-offs between computational efficiency and summarization quality, highlighting the potential benefits of the PEFT approach for resource-constrained environments.

By employing both Fine-Tuning and PEFT methodologies, this study aims to explore the efficacy and practical implications of different training strategies for dialogue summarization tasks. Through empirical evaluation and analysis, we seek to elucidate the strengths and limitations of each approach and provide beneficial perspectives for further studies in natural language processing.

4. RESULTS AND DISCUSSION

Qualitative evaluation involves assessing the coherence and informativeness of the generated summaries through human judgment. Participants are presented with a sample of dialogue summaries produced by each approach and asked to evaluate their quality. Human feedback offers beneficial perspectives into the naturalness and readability of the summaries, assisting in the identification of potential areas for development.

Quantitative evaluation metrics, such as ROUGE scores, are used to assess the similarity between produced and source overviews. provided in the dataset. ROUGE metrics gauge various aspects of summarization quality, including precision, recall, and F1 score, offering objective measures of performance. Comparing ROUGE scores between different approaches yields insights into their summarization effectiveness.

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Example  1
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INPUT PROMPT:

Summarize the following conversation.

#Person1#: What time is it, Tom?
#Person2#: Just a minute. It's ten to nine by my watch.
#Person1#: Is it? I had no idea it was so late. I must be off now.
#Person2#: What's the hurry?
#Person1#: I must catch the nine-thirty train.
#Person2#: You've plenty of time yet. The railway station is very close. It won't take more than twenty minutes to get there.

Summary:

---------------------------------------------------------------------------------------------------
BASELINE HUMAN SUMMARY:
#Person1# is rushing to catch a train but Tom thinks it isn't necessary.
---------------------------------------------------------------------------------------------------
MODEL GENERATION - ZERO SHOT:
The train is about to leave.

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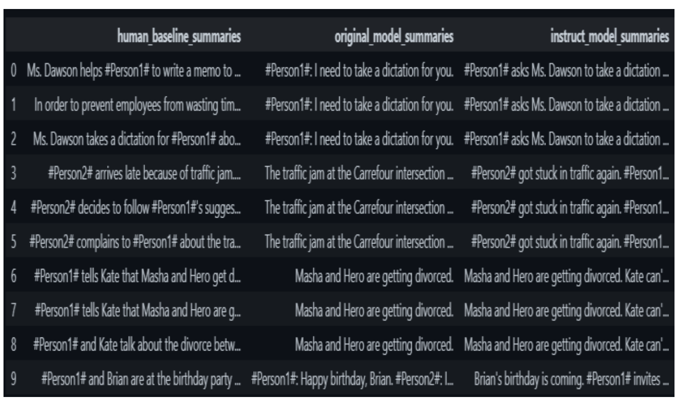

	human_baseline_summaries	original_model_summaries	instruct_model_summaries
0	Ms. Dawson helps #Person1# to write a memo to ...	#Person1#: I need to take a dictation for you.	#Person1# asks Ms. Dawson to take a dictation ...
1	In order to prevent employees from wasting tim...	#Person1#: I need to take a dictation for you.	#Person1# asks Ms. Dawson to take a dictation ...
2	Ms. Dawson takes a dictation for #Person1# abo...	#Person1#: I need to take a dictation for you.	#Person1# asks Ms. Dawson to take a dictation ...
3	#Person2# arrives late because of traffic jam....	The traffic jam at the Carrefour intersection ...	#Person2# got stuck in traffic again. #Person1...
4	#Person2# decides to follow #Person1#'s sugges...	The traffic jam at the Carrefour intersection ...	#Person2# got stuck in traffic again. #Person1...
5	#Person2# complains to #Person1# about the tra...	The traffic jam at the Carrefour intersection ...	#Person2# got stuck in traffic again. #Person1...
6	#Person1# tells Kate that Masha and Hero get d...	Masha and Hero are getting divorced.	Masha and Hero are getting divorced. Kate can'...
7	#Person1# tells Kate that Masha and Hero are g...	Masha and Hero are getting divorced.	Masha and Hero are getting divorced. Kate can'...
8	#Person1# and Kate talk about the divorce betw...	Masha and Hero are getting divorced.	Masha and Hero are getting divorced. Kate can'...
9	#Person1# and Brian are at the birthday party ...	#Person1#: Happy birthday, Brian. #Person2#: I...	Brian's birthday is coming. #Person1# invites ...

Figure 2. Multiple model summaries

In Figure 2, these images accompanying this section include visual representations of quantitative metrics such as providing a comparative analysis of the summarization performance between fine-tuning and PEFT approaches. Additionally, graphs illustrating the scalability and transfer learning capabilities of the models are presented to complement the qualitative and quantitative evaluations.

A comparative analysis between fine-tuning and PEFT is conducted to evaluate their relative performance in dialogue summarization. This analysis considers factors such as computational efficiency, summarization quality, and ease of implementation. By comparing the results obtained from both approaches, researchers can obtain a better knowledge of the advantages and downsides.

The comparative analysis extends beyond quantitative metrics to encompass qualitative aspects such as the interpretability and generalizability of the fine-tuned models. By examining how well the models capture nuanced linguistic nuances and adapt to diverse dialogue contexts, researchers can assess their robustness in real-world applications. Additionally, insights gained from the analysis offered light on the adaptability of the new models to additional NLP tasks, paving the way for more efficient and versatile language understanding systems.

The study explores the potential synergies between fine-tuning and other advanced techniques in NLP, such as transfer learning, domain adaptation, and multi-task learning. By integrating these approaches into the fine-tuning process, researchers can further enhance the performance and scalability of dialogue summarization models. Additionally, the study investigates the role of model architecture and hyperparameter tuning in optimizing the performance of fine-tuned models, offering valuable guidance for practitioners seeking to leverage state-of-the-art NLP techniques for dialogue summarization tasks.

Model	Rouge 1	Rouge 2	Rouge L	Rouge Lsum
Original	0.227	0.070	0.200	0.201
Instruct	0.396	0.172	0.280	0.282
PEFT	0.241	0.118	0.220	0.221

Table 1: Performance Comparison of Models

The Table1 displays the performance indicators of three distinct models in the setting of text summarization evaluation. The models are assessed using four Rouge metrics: Rouge1, Rouge2, RougeL, and RougeLsum. Rouge1 measures overlap of unigrams, Rouge2 measures overlap of bigrams, RougeL considers the longest common subsequence, and RougeLsum is the average of RougeL and RougeL precision. The "Original" row likely represents the baseline performance, while "Instruct" and "PEFT" rows indicate the performance of models named "Instruct" and "PEFT" respectively. The higher the Rouge scores, improves the effectiveness of the model in capturing the content of reference summaries. In this table, it appears that the "Instruct" model outperforms both the "Original" and "PEFT" models across all Rouge metrics.

The findings of the comparative analysis have broader implications for the future development and deployment of dialogue summarization systems in real-world scenarios. By identifying the strengths and limitations of fine-tuning and PEFT, researchers can inform the design of more efficient and effective summarization pipelines tailored to specific application domains. Furthermore, the study underscores the vitality of current research and collaboration in advancing the area of NLP, driving innovation and progress towards more intelligent and context-aware dialogue summarization solutions.

In Figure 3. The results depicted in the graph demonstrate the performance of three different models in generating dialogue summaries, as measured by ROUGE scores. The Original model, despite its baseline nature, still achieves moderate scores across all ROUGE metrics, indicating a reasonable level of summarization quality. In contrast, the Instruct model, which undergoes full fine-tuning, exhibits a significant improvement in ROUGE scores compared to the original model.

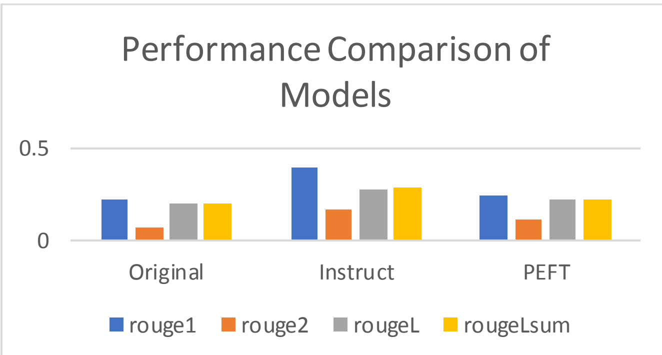

Figure 3. Model Performance Comparison

This enhancement suggests that fine-tuning the model on dialogue summarization data effectively enhances its ability to generate more accurate and informative summaries. Notably, the PEFT model, which utilizes Parameter-Efficient Fine-Tuning, demonstrates comparable performance to the Instruct model, albeit with slightly lower scores in some ROUGE metrics. This suggests that PEFT offers a more efficient approach to fine-tuning, achieving similar summarization quality while requiring fewer computational resources.

It highlights the effectiveness of both fine-tuning and PEFT methodologies in improving the dialogue summarization capabilities of pre-trained LMs. The significant performance gains observed with both approaches underscore their potential to enhance the efficiency and accuracy of dialogue summarization systems. These results offer insightful information to natural language processing academics and practitioners, pointing them in the direction of more successful approaches to the creation and application of dialogue summarization models. Additionally, the comparative analysis between fine-tuning and PEFT sheds light on the trade-offs between computational resources and summarization quality, providing useful advice on how to choose the best strategy depending on the limits and requirements of a certain application.

To evaluate the scalability and robustness of fine-tuning and PEFT, the effect of training data size on their performance is examined. Experiments are conducted using varying amounts of training data to evaluate the generalization capabilities of each approach. Insights gained from this analysis offer guidance on the optimal utilization of training resources for dialogue summarization tasks. The transfer learning performance of fine-tuned and PEFT models is assessed by testing their ability to generalize to unseen dialogues and topics. Models trained on a specific dataset are evaluated on external datasets to measure their adaptability and transferability across different domains. The analysis of transfer learning performance provides valuable insights into the versatility of each approach.

Finally, the key findings of the study are discussed, highlighting the implications of the results for dialogue summarization research and applications. Insights gained from the qualitative and quantitative evaluations, as well as the comparative analysis between fine-tuning and PEFT, are synthesized to provide a comprehensive understanding of the effectiveness of each approach.

5. CONCLUSION

In conclusion, this study has presented an investigation into enhancing dialogue summarization through two distinct methodologies. Through fine-tuning, specifically on the FLAN-T5 model, the study demonstrated the efficacy of modifying previously trained LMs for the dialogue summarization task. Additionally, PEFT, employing Low-Rank Adaptation (LoRA), offered a more resource-efficient approach by training adapter layers while keeping the base model frozen.

Qualitative and quantitative evaluations, including ROUGE scores, highlighted the effectiveness of both approaches in generating accurate and concise summaries of conversational dialogues. While fine-tuning resulted in notable improvements over the original model, PEFT provided comparable performance with significantly lower resource requirements. These findings underscore the potential of both methodologies for advancing dialogue summarization tasks, catering to various computational constraints and use-case scenarios. Further research could explore hybrid approaches that combine the strengths of both fine-tuning and PEFT, providing flexible solutions for a broad spectrum of applications involving natural language processing.

The methodologies explored in this study offer potential applications in various fields, including but not limited to information retrieval, chatbot development, and summarization systems. Additionally, the paper's scope encompasses the evaluation of these methodologies using qualitative and quantitative measures, providing insights into their effectiveness and applicability in different contexts. Through this research, the paper aims to offer practical solutions and insights that can benefit researchers, practitioners, and developers working in the domain of generative AI and dialogue summarization.

REFERENCES

[1]. Ahilan. A, Pradeep Khanth. B, Ezhilarasi. R, Muthukumaran. N, "Efficient luma modification based chroma down-sampling and novel luma down-sampling with adaptive interpolation", Signal, Image and Video Processing, Vol.18, No.2, pp. 1415–1428, 2024.

[2]. Anusha.K, Ajay. P, Ramesh.M, Muthukumaran.N, Rajeshkumar.C, Sangeetha.K, Rajeshkumar.G & Ahilan.A, "HOEEACR: Hybrid Optimized Energy-Efficient Adaptive Clustered Routing for WSN", IETE Journal of Research, Published online, March 2024.

[3]. Anlin Sahaya Infant Tinu. M, Ahilan Appathurai & Muthukumaran.N, "Detection of Brain Tumour Via Reversing Hexagonal Feature Pattern for Classifying Double-Modal Brain Images", IETE Journal of Research, Published online, February 2024.

[4]. Pearce, H., Tan, B., Ahmad, B., Karri, R., & Dolan-Gavitt, B. (2023, May). Examining zero-shot vulnerability repair with large language models. In 2023 IEEE Symposium on Security and Privacy (SP) (pp. 2339- 2356). IEEE.

[5]. Hu, L., Liu, Z., Zhao, Z., Hou, L., Nie, L., & Li, J. (2023). A survey of knowledge enhanced pre-trained LMs. IEEE Transactions on Knowledge and Data Engineering.

[6]. Du, J., Grave, E., Gunel, B., Chaudhary, V., Celebi, O., Auli, M.& Conneau, A. (2020). Self-training improves pre-training for natural language understanding. arXiv preprint arXiv:2010.02194.

[7]. Faiyaz Ahmad, Hariharan.U, Muthukumaran.N, Aleem Ali & Shivi Sharma, "Emotion recognition of the driver based on KLT algorithm and ShuffleNet V2", Signal, Image and Video Processing, Published online, February 2024.

[8]. Gunel, B., Du, J., Conneau, A., & Stoyanov, V. (2020). Supervised contrastive learning for pre-trained LM fine-tuning. arXiv preprint arXiv:2011.01403.

[9]. Su, Y., Han, X., Zhang, Z., Lin, Y., Li, P., Liu, Z., ... & Sun, M. (2021). Cokebert: Contextual knowledge selection and embedding towards enhanced pre-trained LMs. AI Open, 2, 127-134.

[10]. Jiang, H., He, P., Chen, W., Liu, X., Gao, J., & Zhao, T. (2019). Smart: Robust and efficient fine-tuning for pre-trained natural language models through principled regularized optimization.

[11]. Lavanya Kumari. P, Siva. M, Muthukumaran. N, Dharani. D, Kavitha Sahithi. K, Ashwin Kumar. V, "Video Object Forgery Detection using Image Processing Techniques," 7th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Kirtipur, Nepal, 2023, pp. 785-788.

[12]. (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Kirtipur, Nepal, 2023, pp. 524-526.

[13]. Su, J. C., Maji, S., & Hariharan, B. (2020, August). When does selfsupervision improve few-shot learning?. In European conference on computer vision (pp. 645-666). Cham: Springer International Publishing.

[14]. Praveen Kumar.R, Muthukumaran.N, Cheruku Hanisha, Pohar Rithvik, Saipavan Goud.M, "Examination System Automation Using Natural Language Processing," 2023 International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS), Erode, India, 2023, pp. 1002-1008.

[15]. Peng, H., Gao, T., Han, X., Lin, Y., Li, P., Liu, Z.,& Zhou, J. (2020). Learning from context or names? An empirical study on neural relation extraction. arXiv preprint arXiv:2010.01923.

[16]. Rajkumar. K, Hariharan. U, Dhanakoti. V, Muthukumaran. N, 'A secure framework for managing data in cloud storage using rapid asymmetric maximum based dynamic size chunking and fuzzy logic for deduplication', Wireless Network, Volume 30, pages 321–334, January 2024.

[17]. Joshi, M., Chen, D., Liu, Y., Weld, D. S., Zettlemoyer, L., & Levy, O. (2020). Spanbert: Improving pre-training by representing and predicting spans. Transactions of the association for computational linguistics, 8, 64- 77

[18]. Zhang, Y., Sun, S., Galley, M., Chen, Y. C., Brockett, C., Gao, X., & Dolan, B. (2019). Dialogpt: Large-scale generative pre-training for conversational response generation. arXiv preprint arXiv:1911.00536.