MarketMinds : Unleashing Marketing Insights Through LLM

Umesh Nehete
Computer Science and Engineering
Data Science
PCT's A. P. Shah Institute of Technology
Thane, India
umeshnehete646@apsit.edu.in

Prof. Sarala Mary
Teaching Staff of Department of CSE (Data Science),
A.P. Shah Institute of Technology,
Thane (M.H), India 400615
Email:

Harshad Raurale
Computer Science and Engineering
Data Science
PCT's A. P. Shah Institute of Technology
Thane, India
harshadraurale643@apsit.edu.in

Saaras Gaikwad
Computer Science and Engineering
Data Science
PCT's A. P. Shah Institute of Technology
Thane, India
saarasgaikwad644@apsit.edu.in

Priyanshu Worlikar
Computer Science and Engineering
Data Science
PCT's A. P. Shah Institute of Technology
Thane, India
priyanshuworlikar642@apsit.edu.in

***Abstract*— This project focuses on utilizing advanced neural network techniques, specifically the Llama-2 model built on Transformers architecture, to generate descriptive captions for company products. By training on extensive datasets, this model demonstrates proficiency in creating contextually relevant captions, improving product visibility and understanding. Additionally, the project includes competitor analysis based on Instagram engagement metrics, allowing businesses to gain insights into competitor performance and audience preferences. Through the fusion of deep learning technologies and data-driven analysis, the project aims to revolutionize product marketing strategies, empowering businesses to enhance competitiveness in the market. Furthermore, by leveraging data analytics techniques, this project enables businesses to refine their marketing strategies and optimize audience engagement based on comprehensive competitor insights. Ultimately, this integration of cutting-edge technology and data-driven analysis promises to redefine product marketing paradigms and foster sustained growth in competitive markets.**

Keywords—Tag-based recommendations, cosine similarity, collaborative filtering, content-based filtering, and personalization.

I. Introduction

In today's digital age, the convergence of cutting-edge technologies has paved the way for innovative solutions in the realms of natural language processing and social media analytics. Our project represents a synergistic fusion of these disciplines, with a primary focus on caption generation using the Llama-2 model within the transformative framework of Transformers architecture in neural networks. Additionally, our project extends its purview to encompass a comprehensive analysis of competitors' social media presence, leveraging engagement metrics such as likes and comments on Instagram posts. The rapid proliferation of visual content across various digital platforms has underscored the importance of effective textualdescriptions to enhance user engagement and comprehension. Caption generation has emerged as a pivotal tool in this algorithm accessing this is a regard, enabling businesses to provide contextually relevant and engaging descriptions for their products and services. Leveraging the powerful capabilities of the Llama-2 model, our project endeavors to push the boundaries of caption generation, offering a sophisticated solution that transcends conventional methodologies.

The Llama-2 model, built upon the robust Transformers architecture, represents a quantum leap in natural language processing capabilities. Trained on vast repositories of textual data, Llama-2 demonstrates remarkable proficiency in understanding and generating coherent and contextually relevant captions. By harnessing the power of this advanced model, our project aims to empower businesses to create compelling textual descriptions that resonate with their target audience, thereby enhancing product visibility and comprehension.

Furthermore, our project recognizes the importance of strategic intelligence in today's competitive landscape. In addition to caption generation, we delve into the realm of competitor analysis, leveraging engagement metrics gleaned from Instagram posts to unravel insights into competitors' performance, audience preferences, and content strategies. By employing sophisticated data analytics techniques, our project equips businesses with actionable insights to refine their marketing approaches, optimize audience engagement, and maintain a competitive edge in the dynamic arena of social media marketing.

Through the seamless integration of advanced neural network technologies and data-driven analysis, our project seeks to redefine the paradigm of product marketing, offering businesses a comprehensive toolkit to enhance their online presence and competitiveness. As we embark on this journey at the intersection of artificial intelligence and social media analytics. The project acknowledges the importance of strategic intelligence in today's competitive landscape, highlighting the need for businesses to understand their competitors and market trends to stay ahead. By integrating advanced neural network technologies, the project aims to offer businesses a comprehensive toolkit for enhancing their online presence and competitiveness. This indicates a focus on leveraging cutting-edge AI technologies to provide innovative solutions. he projects employs sophisticated data analytics techniques to process the gathered information.

II. LITERATURE REVIEW

In the ever-evolving landscape of recommendation systems, a multitude of research papers have emerged to advance our understanding and improve user experiences.

“Generating Campaign Ads & Keywords for Programmatic Advertising” [1] Experimenting with different ads and keywords is usual practice in search marketing. Advertisers pause underperforming keywords and ads of a search campaign, and replace them with better alternatives. Therefore, new ads and keywords need to be produced easily for effective campaign management. We built GeNN for generating campaign ads and keywords programmatically. GeNN is based on language modeling. Using the existing keywords of a campaign as input, our GPT-2 based generator created novel keywords of good quality with a high number of expected clicks and conversions according to the forecast data provided by Google’s keyword planner. Using the product landing page and sample ad copies as input, our GPT-2 based summarizer was able to generate production-ready ads. One of the ads that was tested for two weeks in a real search campaign had a CTR of 6% and converted real users. Finally, we compared GeNN’s ad performance with a recent method based on two encoder-decoder RNNs being used in parallel; GeNN outperformed this method.

“Llama 2: Early Adopters' Utilization of Meta's New Open-Source Pretrained Model” [2] The AI field sees ongoing innovation with the introduction of open-source pre-trained models like Llama 2 by Meta. This paper explores Llama 2's features and how early adopters use it in their projects. Through a qualitative study, we examine their perspectives and strategies, highlighting strengths, weaknesses, and areas for improvement. Insights from this study benefit both the AI community and Meta in refining future model versions. We also discuss Llama 2's impact on open-source AI, outlining challenges and opportunities for developers and researchers. This study serves as an early exploration of Llama 2, promising further research avenues.

“Llama 2: Open Foundation and Fine-Tuned Chat Models” [3] Llama 2, a set of pretrained large language models (LLMs) ranging from 7 billion to 70 billion parameters. Our fine-tuned LLMs, named Llama 2-Chat, are designed for dialogue tasks and surpass other open-source chat models in most benchmarks. Human evaluations suggest they could serve as alternatives to closed-source models. We provide details on our fine-tuning approach and safety enhancements to encourage community collaboration and responsible LLM development.

“Transformers in Machine Learning” [4] This study explores methods in Transformer Machine Learning, focusing on their versatility and applications. Transformers, neural network architectures, are extensively used across various studies, such as text compression, chemical image recognition with 96% accuracy, and emotion detection in social media conversations. The study aims to review literature from different journals discussing transformers' applications, presenting subjects, datasets, data analysis methods, years, and achieved accuracies. Researchers can use these methods to draw conclusions and identify opportunities for further research.

“A COMPREHENSIVE SURVEY ON APPLICATIONS OF TRANSFORMERS FOR DEEP LEARNING TASKS” [5] The transformer, a deep neural network with self-attention, excels in understanding sequential data. It's gained attention in AI for its ability to handle long dependencies and enable parallel processing. Our survey from 2017 to 2022 highlights its applications in NLP, computer vision, audio processing, healthcare, and IoT. We analyses influential transformer- based models in these areas to provide insights for researchers and enhance understanding of this transformative technology.

III. ARCHITECTURE

In this chapter, we delve into the core components and mechanisms of our recommendation system. We'll explore how user interests are dynamically generated and updated through the Score Generator and how user feedback is incorporated to enhance accuracy. Additionally, we'll uncover the intricate process of recommendation generation, which leverages both collaborative filtering and content-based filtering for optimal results. This chapter provides a comprehensive understanding of the system's architecture, setting the stage for a detailed analysis of its performance and effectiveness in subsequent sections.

Data Collection and Preprocessing:

• Data Collection: Gather a diverse and extensive corpus of text data from various sources relevant to the target domain, including books, articles, social media posts, and websites.

• Preprocessing: Preprocess the raw text data to ensure uniformity and cleanliness. Steps may include removing special characters, lowercasing, and handling punctuation. Additionally, segment the text into smaller units such as words or subwords through tokenization.

• Tokenization: Utilize tokenization techniques such as WordPiece or Byte Pair Encoding (BPE) to break down the text into tokens. This process creates a vocabulary of tokens that the model can understand and process effectively.

• Equation: Tokenization can be represented as:

tokens=tokenizer(raw_text)tokens=tokenizer(raw_text)

Model Architecture:

LLM (Large Language Model):

• Definition: LLMs are deep learning models trained on large text corpora to understand and generate human-like text. They leverage vast amounts of data and powerful computational resources to learn the nuances of language. LLM can refer to several different things depended.

• Training: LLMs like GPT (Generative Pre-trained Transformer) are trained using unsupervised learning techniques on massive text datasets. They learn to predict the next word in a sequence given the context provided by preceding words.

• Application: LLMs have various applications in natural language processing tasks such as text generation, translation, summarization, and sentiment analysis. In our project we have used LLM of text Generation. We generate text based on some questions asked to the user.

• LLAMA2 (Large Language Model for Advanced Applications):

• Definition: LLAMA2 is an advanced version of a large language model developed by Meta (formerly Facebook). It comprises a collection of pre-trained and fine-tuned LLMs optimized for specific tasks or domains.

• Fine-tuning: LLAMA2 includes fine-tuned LLMs tailored for specific use cases, such as dialogue generation (LLAMA2-Chat). These models undergo additional training on task-specific datasets to enhance their performance on specific tasks. In our case we have trained the llama2 mode on the advertisement dataset, so that the appropriate caption for the products/Brands is generated.

• Performance: LLAMA2 models often outperform open-source alternatives on various benchmarks, demonstrating their effectiveness in real-world applications such as chatbots, text summarization, and question answering.

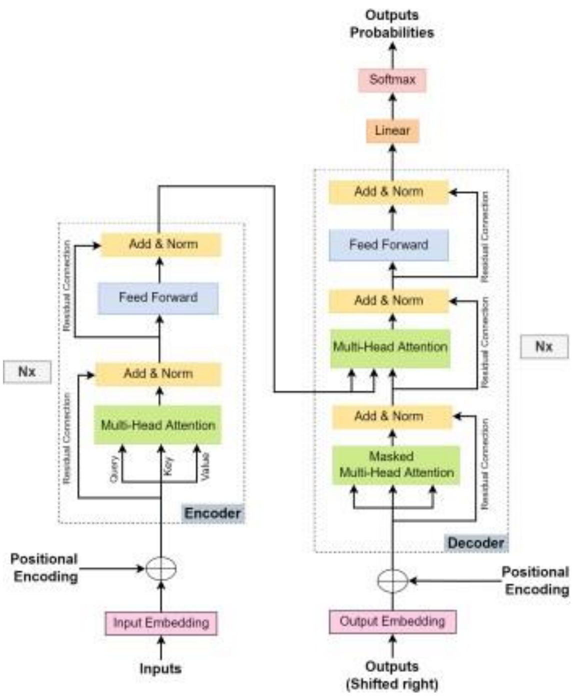

Fig 3.1 Transformer Model

• Transformer Backbone: Adopt the Transformer architecture as the core model structure. Transformers consist of encoder and decoder stacks, each containing multiple layers of self- attention and feed-forward neural networks.

• Transformer (Neural Network Architecture): Transformers are neural network architectures that are considered as inputs. Transformers are widely used in various studies with various objects. The transformer is one of the deep learning architectures that can be modified. Transformers are also mechanisms that study contextual relationships between words. Transformers are used for text compression in readings. Transformer to detect emotions in social media conversations.

• Attention Mechanisms: Leverage attention mechanisms within the Transformer architecture to enable the model to focus on relevant parts of the input sequence when generating output tokens. Self-attention allows the model to capture long-range dependencies efficiently. The utilization of multi-head attention facilitates the neural network in learning and capturing diverse characteristics of the input sequential data. Consequently, this enhances the representation of the input contexts, as it merges information from distinct features of the attention mechanism within a specific range, which could be either short or long. This approach allows the attention mechanism to jointly function, which results in better network performance

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^{\top}}{\sqrt{D_k}}\right)\mathbf{V} = \mathbf{A}\mathbf{V},$$

$$\text{MultiHeadAttn}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{Concat}(\text{head}_1, \ldots, \text{head}_H)\mathbf{W}^O,$$
$$\text{where head}_i = \text{Attention}(\mathbf{Q}\mathbf{W}_i^Q, \mathbf{K}\mathbf{W}_i^K, \mathbf{V}\mathbf{W}_i^V).$$

• Application: In our project we have used llama2 model which is based on transformers architecture. Using the transformers architecture, we are generating the related caption.

IV. RESULT AND ANALYSIS

In this section, we delve into the results and analysis of our text generation system architecture described in the previoussection. We begin by presenting the outcomes of the text generation process.

The process of text generation utilizing Transformer architecture involves several stages, each crucial for producing coherent and contextually relevant output based on user input. These stages are meticulously designed to ensure the effective utilization of the Transformer model's capabilities. Let's explore each stage:

Preprocessing Input: The initial stage involves preprocessing the user input. This typically includes tokenization, where the input text is broken down into individual tokens or words. Additionally, any necessary formatting or encoding steps are applied to prepare the input for further processing.

Model Encoding: In this stage, the pre-processed input isfed into the Transformer model for encoding. The

$$f(x) = \frac{2\sqrt{2}cosx}{cos\frac{x}{2} - sin\frac{x}{2}}$$

$$f(x) = \frac{2\sqrt{2}cosx}{sin^{x} - sin^{x}}$$

Transformer architecture employs multiple layers of self-attention mechanisms, allowing the model to capture intricate patterns and dependencies within the input text.

$$\mathcal{E}(x) = \int d^3k \sqrt{\frac{2\omega}{(2\pi)^3}} \left\{ \begin{array}{c} c^3(e_3+e_4)]e^{-ikx}+ \\ [c^{*2}e_1 + c^{*4}(e_3+e_4)]\,e^{ikx} \end{array} \right\},\ \omega \equiv \sqrt{\vec{k}^2}$$

Contextual Encoding: Following the initial encoding, the Transformer model generates contextual embeddings for each token in the input sequence. These embeddings encapsulate both the token's semantic meaning and its contextual relationships with surrounding tokens, enabling the model to understand the nuances of the input text.

$$\mathcal{E}(x) = \int d^3k \sqrt{\frac{2\omega}{(2\pi)^3}} \left\{ \begin{array}{c} [c^1e_1 + c^3(e_3+e_4)]\,e^{-ikx}+ \\ [c^{*2}e_1 + c^{*4}(e_3+e_4)]\,e^{ikx} \end{array} \right\},\ \omega \equiv \sqrt{\rightarrow k^2}$$

Generation Process: Once the input is encoded and contextualized, the generation process begins. At this stage, the Transformer model utilizes its learned representations to generate new text based on the input context. This involves iteratively predicting the most probable next token given the preceding tokens, effectively generating coherent and contextually relevant output.

$$f'_N = \left\{ \pi^{-1/2} \sum_{n=0}^{N} \frac{(-1)^n}{n!} \left(\frac{\lambda}{4}x^4\right)^n e^{-x^2}\ for\,|x| < x_{c,N} 0 for\,|x| > x_{c,N} \right.$$

$$f'_N = \left\{ \pi^{-1/2} \sum_{n=0}^{N} \frac{(-1)^n}{(n)} \left(\frac{\lambda}{4}x^4\right)^n e^{-x^2}\ for\,|x| < x_{c,N} 0 for\,|x| > x_{c,N} \right.$$

Sampling Strategy: To enhance the diversity and creativity of the generated text, a sampling strategy is employed. This strategy determines how the model selects the next token during the generation process. Techniques such as temperature scaling or nucleus sampling may be utilized to control the randomness of token selection and encourage theproduction of varied and interesting output.

Post-processing: Finally, the generated text undergoes post- processing to ensure readability and coherence. This may involve removing any special tokens or unwanted artifacts introduced during the generation process, as well as applying formatting or stylistic adjustments as needed. During the generation process, special tokens or unwanted artifacts may be introduced, such as placeholders for variables or tokens indicating the end of a sequence. Post-processing involves removing these tokens to produce clean and readable text. Apart from special tokens, other artifacts like repetitive phrases, nonsensical sequences, or grammatical errors may appear in the generated text. Post-processing can involve identifying and removing such artifacts to improve the overall quality of the output. Post-processing may also involve polishing the language to make it more polished and natural-sounding. This may include adjusting word choice, refining sentence structures, and enhancing overall linguistic fluency to produce text that reads more smoothly and convincingly. Post-processing may include performing grammar and spelling correction to fix any grammatical errors, typos, or misspelled words in the generated text. This step is essential for improving the overall linguistic quality and coherence of the output.

1. User will Login into the system, if registration exits.

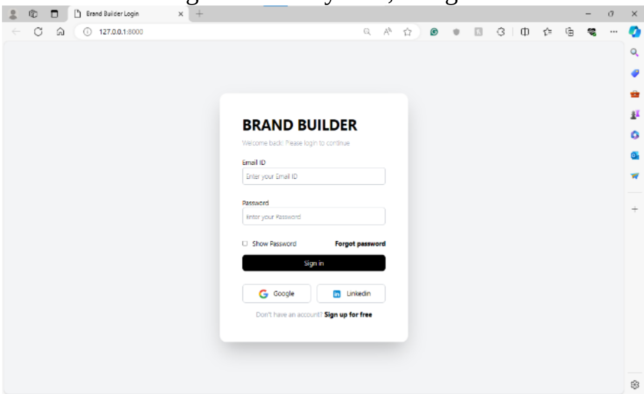

Fig.4.1 Login Page.

2. If user is using first time system, has register with product name and product category.

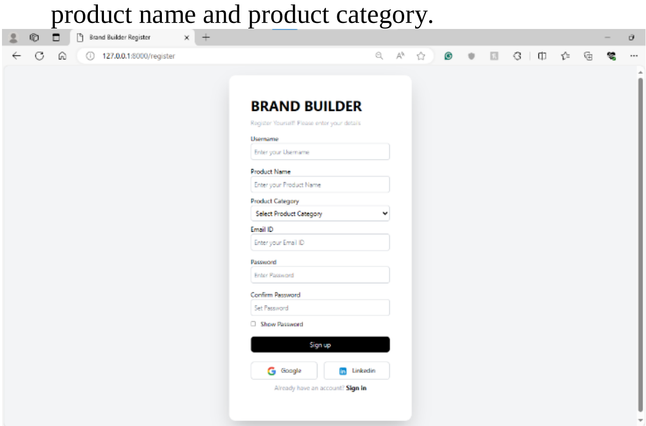

Fig 4.2 Registration Page.

3. User can filter the product the category.

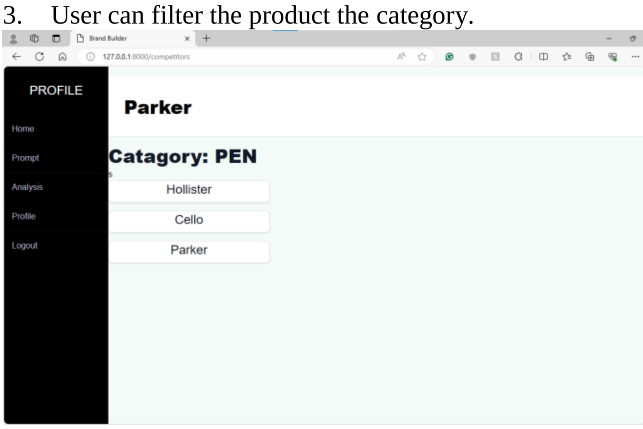

Fig 4.3 Product filtering on the bases of category.

4. User can view his product analysis on the basis of social media Likes, Shares and comment. As well competitor's post likes, shares and comments.

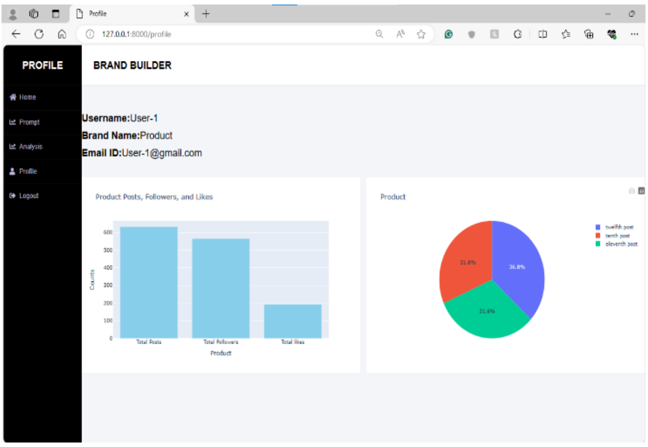

Fig 4.3 Product Analysis.

5. User can do competitor analysis of own product and competitor's product for better improvement on social Media engagement.

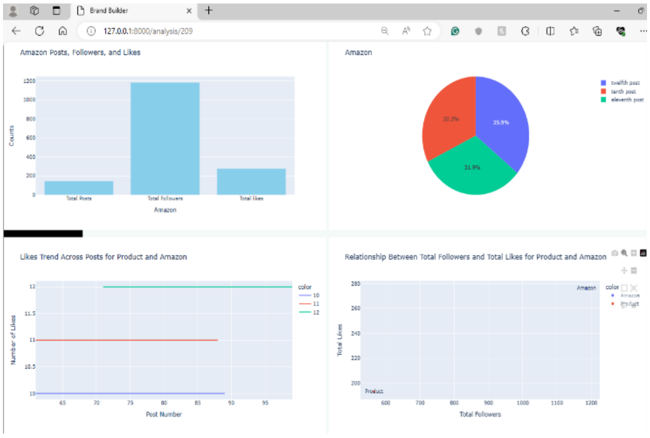

Fig 4.4 Competitor analysis.

6. Depending on answer of this question, the prompt is generated with hashtag. User can use this prompt as caption of Instagram, LinkedIn post.

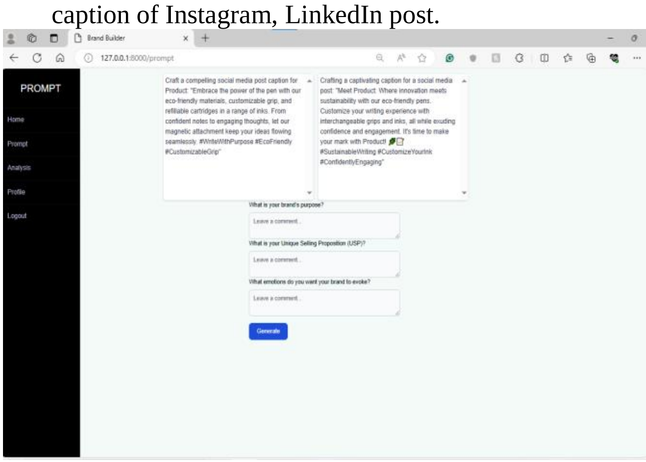

Fig 4.5 Prompt generation.

V. CONCLUSION

In conclusion, Large Language Models (LLMs), the Transformer architecture, and LLAMA2 signify significant milestones in the progression of Natural Language Processing (NLP) and Artificial Intelligence (AI). Their versatility, scalability, and performance have propelled the field forward, offering novel avenues for intelligent text processing and comprehension. These advancements have empowered researchers and practitioners to address intricate NLP tasks with greater efficacy, resulting in notable breakthroughs across various domains including human-computer interaction, content generation, and information retrieval. Moreover, as ongoing innovation and refinement efforts persist in these technologies, we anticipate further breakthroughs and advancements that will continue to shape the landscape of AI-driven language understanding and generation, heralding an era of increasingly sophisticated and capable NLP systems.

In summary, our application based on LLAMA2, Large Language Models (LLMs), and the Transformer architecture represents a significant leap forward in the development of text generative models. As a result, it not only enables the generation of human-like text across diverse domains but also opens up new possibilities for creative content creation, storytelling, and language understanding. Moving forward, continued refinement and innovation in these technologies promise to drive further advancements in AI-driven text generation, ultimately reshaping the landscape of natural language processing and communication.

REFERENCS

[1] Truhn, Daniel, et al. "Large language models and multimodal foundation models for precision oncology." (Published in partnership with The Hormel Institute, University of Minnesota) NPJ Precision Oncology 8.1 72: (2024).

[2] Roumeliotis, Konstantinos I., Nikolaos D. Tselikas, and Dimitrios K. Nasiopoulos. "Llama 2: Early-adopter Utilization of Meta's New Open-Source Pretrained Model" (2023).

[3]Touvron, Hugo, et al. "Llama 2: Open foundation and fine-tuned chat models." arXiv preprint Xiv:2307.09288 (2023).

[4] Islam, Saidul, et al. "A comprehensive survey on applications of transformers for deep learning tasks." Expert Systems with Applications (Elsevier): 122666 (2023).

[5] Thoyyibah, T., et al. "Transformers in Machine Learning: Literature Review." Jurnal Penelitian Pendidikan IPA 9.9 Journal of Research in Science Education (2023): 604-610.