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Next-Gen Pharma Communication: Revolutionizing Doctor-Pharma Relationships Using AI-Driven Messaging & Insights

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Abstract: The pharmaceutical industry is a highly competitive industry which strives to build strong, meaningful relationships with doctors but, often struggles to maintain meaningful and timely communication with doctor's post-meetings. Conventional engagement strategies such as manual post-visit communication is time-consuming, inconsistent, and lacks personalization and often results in generic interactions, reducing the impact of medical representatives' efforts and brand recall. To increase timely and relevant interactions between the pharmaceutical representatives and doctors, we aim to create an AI-driven post-visit messaging service that proactively improves engagement via automated bespoke messages responding to the representative's conversation with the doctor. The proposed solution integrates LLaMA 3 (Large Language Model Meta AI), the system is fine-tuned to understand the sentiment and intent and learns from previous pharma representative inputs and generates personalized thank you or feedback messages based on the pharma representative's input. The AI model ensures messages remain highly professional, relevant, and aligned with brand guidelines. A standalone application for the existing pharma company app that the representatives would deploy is created. Minimal post-visit feedback is provided by the representative to be converted by the model using tuned NLU (Natural Language Understanding), which it integrates with. The structured answer is transformed into a message using dynamic AI featurette system, and sent out through available email, SMS, or WhatsApp thus closing the engagement loop. The entire system is fully automated, guaranteeing compliance while maximizing efficiency. The system maximizes engagement and trust by ensuring every interaction correlates with the representative's message, thus building long lasting relationships with the doctors, and enables the company to stand out in a crowded market, strengthening the firm's dedication to authentic relationships with physicians which ultimately enhances the company's competitive advantage. Encourage effective communication using AI personalization's builds trust and dramatically changes market penetration and physician retention.

***Keywords**: AI-Driven Messaging, Personalized Interaction Strategy, Llama 3 Fine-Tuning, NLU (Natural Language Understanding), Python Dynamic Message, Doctor Engagement, Brand Recall & Trust.*

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I. INTRODUCTION

The pharmaceutical industry is one of the most dynamic and competitive industries in the world that operates under strict regulations and therefore proper and effective communication with doctors is very important and at the same time highly challenging. The traditional approach to post-meeting engagement, where medical representatives manually follow up with doctors via calls, emails, or text messages, is often time-consuming, inconsistent, and lacks personalization [1]. This leads to the generation of generic responses that fail to resonate with physicians, ultimately diminishing the impact of medical representative's efforts, time and reducing overall brand recall [2]. Additionally, the entire process is made further complex by compliance issues, as the pharmaceutical companies must ensure that all communication remains professional, ethical, and within the boundaries of regulatory frameworks [3]. In an era where

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efficiency, engagement, and personalization are critical factors in customer relationships, the need for a more intelligent, automated, and scalable solution is evident.To overcome these challenges, we propose a post-visit messaging system that is AI-based and sends dynamically framed messages to doctors based on the meeting feedback and topic of discussion by leveraging state-of-the-art Natural Language Processing (NLP) and sentiment analysis to generate personalized, contextual, and regulation-compliant messages for doctors after each interaction [4]. This system integrates advanced AI models, including LLaMA 3 (Large Language Model Meta AI), which has been fine-tuned using LoRA (Low-Rank Adaptation) techniques on a dataset of structured feedback from the pharmaceutical representatives. Thus, the AI understands the purpose and the sentiment of the representative's input and creates the responses that are quite professional and relevant to the situation while not violating the pharmaceutical industry rules [5]. These messages are not generic automated responses but are intelligently crafted to reflect the nuances of each doctor-representative interaction, ensuring that every follow-up feels personalized, relevant, and valuable to the recipient.

This system is also characterized by the fact that it can be easily combined with the current applications of the pharmaceutical companies and communication channels, such as email, SMS, and WhatsApp, allowing representatives to automate their follow-ups while maintaining a human-like touch. It is not just thank you messages or feedback response that the AI creates but also learns from past interactions to optimize future interactions. Moreover, the AI approach excludes unnecessary calls and messages, which are stressful for doctors while maintaining a consistent presence, and strengthening long-term relationships between the pharmaceutical companies and healthcare professionals.

To improve the effectiveness of the messages that are generated, the AI uses advanced Natural Language Understanding (NLU) features to try to understand any form of input from the representatives and produce meaningful and organized responses in its output. This ensures that representatives do not need to spend excessive time providing detailed feedback, as the AI can infer context and generate responses accordingly. Furthermore, the system is designed to be scalable and future-proof such that it can be continually tuned on more real-time pharma-specific messages like thank you notes, feedback-based responses, or ratings. This flexibility means that the system can be updated to meet new industry standards and communication practices.

In addition to the direct contact rate, the AI-based system also helps to increase the productivity of sales and marketing departments in the pharmaceutical companies. The medical representatives thus released from the burden of documenting the post-visit activities can engage in more critical activities for example, direct contact with the doctors and planning. This results in better resource allocation, higher-quality interactions, and improved overall visit outcomes. Also, the use of personalization through AI ensures that the brand is positioned to be more memorable to the doctors since the messages that the doctors receive are relevant to the discussions that they had during the meeting. This strengthens physician-pharma relationships, and the company is perceived and positioned as a partner that is concerned with the transmission of healthcare information.

Technically, the system is built on a robust pipeline for compliance, scalability, and adaptability. The use of LLaMA 3 in 4-bit quantized mode makes sure that the AI model is lightweight yet powerful in the language generation task. The dynamic AI messaging system that operates using Python ensures that responses are consistent and comply with the brand standards. The system has the potential to be implemented and expanded in the near future by integrating with EHR (Electronic Health Records) or pharmaceutical CRM (Customer Relationship Management) tools. This integration would enable smarter communication strategies that align with patient histories and doctor preferences, enhancing the overall healthcare experience and improving personalized treatment plans. The AI continuously analyses the engagement data and makes recommendations for improving message delivery to increase the response rates without having to follow up with the doctors repeatedly.

In addition to improving the effectiveness of the interactions, the adoption of this post-visit messaging system based on AI provides several benefits to the pharmaceutical companies. The optimization of the communication with doctors improves the general perception of the brand and provides customers with a consistent and professional communication channel. By replacing inconsistent manual outreach with AI-powered personalized messaging, the pharmaceutical firms can establish themselves as trusted, forward-thinking partners in healthcare communication. This in turn leads to higher physician loyalty, higher brand recognition and more engagement with the doctors in the long run. Furthermore, with the help of the AI, companies can gain insights into the consumption behaviour of physicians and, therefore, improve their communication strategies and increase the response rates of the messages sent.

From an organizational perspective, this AI solution enhances the work of medical representatives, thus allowing them to concentrate on important activities like planning and more engaged work with the most important healthcare practitioners. It reduces the administrative burdens and prevents unnecessary follow-ups that would otherwise be made. Furthermore, in the near future, the company can seamlessly integrate the CRM systems and the current EHR platforms, which will help the pharmaceutical companies to have an overall view of the doctors' interactions and better utilization of resources. This data-driven approach not only improves the efficiency of sales and marketing strategies but also drives measurable business growth, positioning the company at the forefront of AI-powered healthcare engagement.

This data-driven approach not only improves the efficiency of sales and marketing strategies but also leads to quantitative business growth and, therefore, places the company at the head of the AI-powered healthcare companies. With the integration of LLaMA 3 and LoRA tuning, the system is improved to achieve compliance, effectiveness, and personalization at scale. We will delve into

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the advanced technologies and methodologies driving the transformation and offering an in-depth exploration, and shaping the future sentiment analysis and language generation for the pharmaceutical communication, in the following section.

II. METHOD & METHODOLOGY

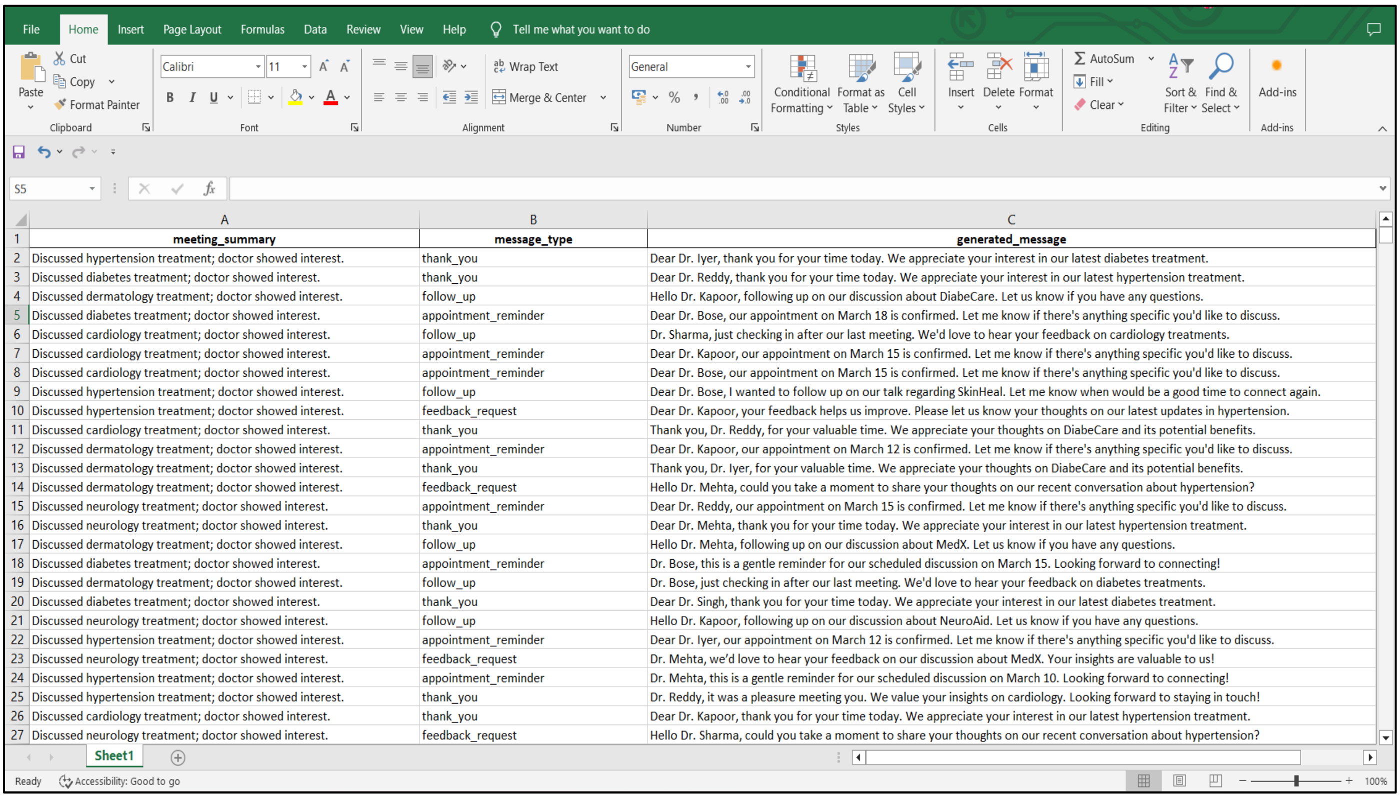
Our AI powered follow up messaging system went through multiple phases. Starting from gathering and preparing data to training the model and refining it before putting it into action, in real time settings. Considering the complexity of the sector and the requirement, for personalized messages that are highly compliant and contextually relevant to the individual's needs; our approach emphasized maintaining high data accuracy from the beginning to ensure effective training and smooth integration, for adapting in real time environments. The approach consisted of two major parts: Phase 1: Data Collection, Pre-processing, and Model Training, followed by Phase 2: Dynamic Message Generation and Real-Time Integration. Each component played a crucial role, in improving the AIs capability to boost interaction within the pharmaceutical sector while upholding compliance, with industry standards.

A. *Phase 1: Data Collection, Pre-Processing, and Model Training*

To develop an AI model that can grasp the details, in the pharmaceutical communication effectively we had to start by obtaining a top-notch dataset. Upon our request few prominent Indian pharmaceutical companies generously shared their real-life post meeting feedback information, for our study. However, each company had stored its data in distinct formats, which presented challenges during the data pre-processing stage [6]. Companies provided structured spreadsheets with separate columns for product discussions and doctor responses, offered semi-structured CSV files with missing values, and highly detailed reports containing additional metadata such as timestamps, representative IDs, and visit durations [7]. Due to these sorts of multiple variations, in data formats received from sources we had to create a data cleaning process involving multiple steps to ensure consistency and standardization across the dataset.

➤ *The Data Cleaning Process Involved:*

- Handling missing values – Empty or incomplete fields were either filled using techniques that consider the context as relevant or removed if the information provide was not useful.
- Standardizing text formats – Standardizing text formats involves making sure that all messages have a structure by adjusting capitalization where needed and eliminating punctuation marks and shorthand notations.
- Concatenating multi-field inputs – Since some datasets had messages split across multiple columns, we merged relevant fields into single structured sentences.
- Filtering unwanted data – During the training process, for post visit messaging analysis we made sure to exclude any information (e.g., internal company notes, timestamps) was removed to avoid biases during training).
- Ensuring consistency in representative inputs – Ensuring that there is consistency in the way representative inputs are handled was crucial, for companies because some of them presented doctor names and titles in formats (e.g., "Dr. John" vs. "John, MD"). This demanded additional formatting to meet industry norms.



	meeting_summary	message_type	generated_message
2	Discussed hypertension treatment; doctor showed interest.	thank_you	Dear Dr. Iyer, thank you for your time today. We appreciate your interest in our latest diabetes treatment.
3	Discussed diabetes treatment; doctor showed interest.	thank_you	Dear Dr. Reddy, thank you for your time today. We appreciate your interest in our latest hypertension treatment.
4	Discussed dermatology treatment; doctor showed interest.	follow_up	Hello Dr. Kapoor, following up on our discussion about DiabeCare. Let us know if you have any questions.
5	Discussed diabetes treatment; doctor showed interest.	appointment_reminder	Dear Dr. Bose, our appointment on March 18 is confirmed. Let me know if there's anything specific you'd like to discuss.
6	Discussed cardiology treatment; doctor showed interest.	follow_up	Dr. Sharma, just checking in after our last meeting. We'd love to hear your feedback on cardiology treatments.
7	Discussed cardiology treatment; doctor showed interest.	appointment_reminder	Dear Dr. Kapoor, our appointment on March 15 is confirmed. Let me know if there's anything specific you'd like to discuss.
8	Discussed cardiology treatment; doctor showed interest.	appointment_reminder	Dear Dr. Bose, our appointment on March 15 is confirmed. Let me know if there's anything specific you'd like to discuss.
9	Discussed hypertension treatment; doctor showed interest.	follow_up	Dear Dr. Bose, I wanted to follow up on our talk regarding SkinHeal. Let me know when would be a good time to connect again.
10	Discussed hypertension treatment; doctor showed interest.	feedback_request	Dear Dr. Kapoor, your feedback helps us improve. Please let us know your thoughts on our latest updates in hypertension.
11	Discussed cardiology treatment; doctor showed interest.	thank_you	Thank you, Dr. Reddy, for your valuable time. We appreciate your thoughts on DiabeCare and its potential benefits.
12	Discussed dermatology treatment; doctor showed interest.	appointment_reminder	Dear Dr. Kapoor, our appointment on March 12 is confirmed. Let me know if there's anything specific you'd like to discuss.
13	Discussed dermatology treatment; doctor showed interest.	thank_you	Thank you, Dr. Iyer, for your valuable time. We appreciate your thoughts on DiabeCare and its potential benefits.
14	Discussed dermatology treatment; doctor showed interest.	feedback_request	Hello Dr. Mehta, could you take a moment to share your thoughts on our recent conversation about hypertension?
15	Discussed neurology treatment; doctor showed interest.	appointment_reminder	Dear Dr. Reddy, our appointment on March 15 is confirmed. Let me know if there's anything specific you'd like to discuss.
16	Discussed neurology treatment; doctor showed interest.	thank_you	Dear Dr. Mehta, thank you for your time today. We appreciate your interest in our latest hypertension treatment.
17	Discussed dermatology treatment; doctor showed interest.	follow_up	Hello Dr. Mehta, following up on our discussion about MedX. Let us know if you have any questions.
18	Discussed diabetes treatment; doctor showed interest.	appointment_reminder	Dr. Bose, this is a gentle reminder for our scheduled discussion on March 15. Looking forward to connecting!
19	Discussed dermatology treatment; doctor showed interest.	follow_up	Dr. Bose, just checking in after our last meeting. We'd love to hear your feedback on diabetes treatments.
20	Discussed diabetes treatment; doctor showed interest.	thank_you	Dear Dr. Singh, thank you for your time today. We appreciate your interest in our latest diabetes treatment.
21	Discussed neurology treatment; doctor showed interest.	follow_up	Hello Dr. Kapoor, following up on our discussion about NeuroAid. Let us know if you have any questions.
22	Discussed hypertension treatment; doctor showed interest.	appointment_reminder	Dear Dr. Iyer, our appointment on March 12 is confirmed. Let me know if there's anything specific you'd like to discuss.
23	Discussed neurology treatment; doctor showed interest.	feedback_request	Dr. Mehta, we'd love to hear your feedback on our discussion about MedX. Your insights are valuable to us!
24	Discussed hypertension treatment; doctor showed interest.	appointment_reminder	Dr. Mehta, this is a gentle reminder for our scheduled discussion on March 10. Looking forward to connecting!
25	Discussed hypertension treatment; doctor showed interest.	thank_you	Dr. Reddy, it was a pleasure meeting you. We value your insights on cardiology. Looking forward to staying in touch!
26	Discussed cardiology treatment; doctor showed interest.	thank_you	Dear Dr. Kapoor, thank you for your time today. We appreciate your interest in our latest hypertension treatment.
27	Discussed neurology treatment; doctor showed interest.	feedback_request	Hello Dr. Sharma, could you take a moment to share your thoughts on our recent conversation about hypertension?

Fig 1: Structured Dataset after Pre-Processing

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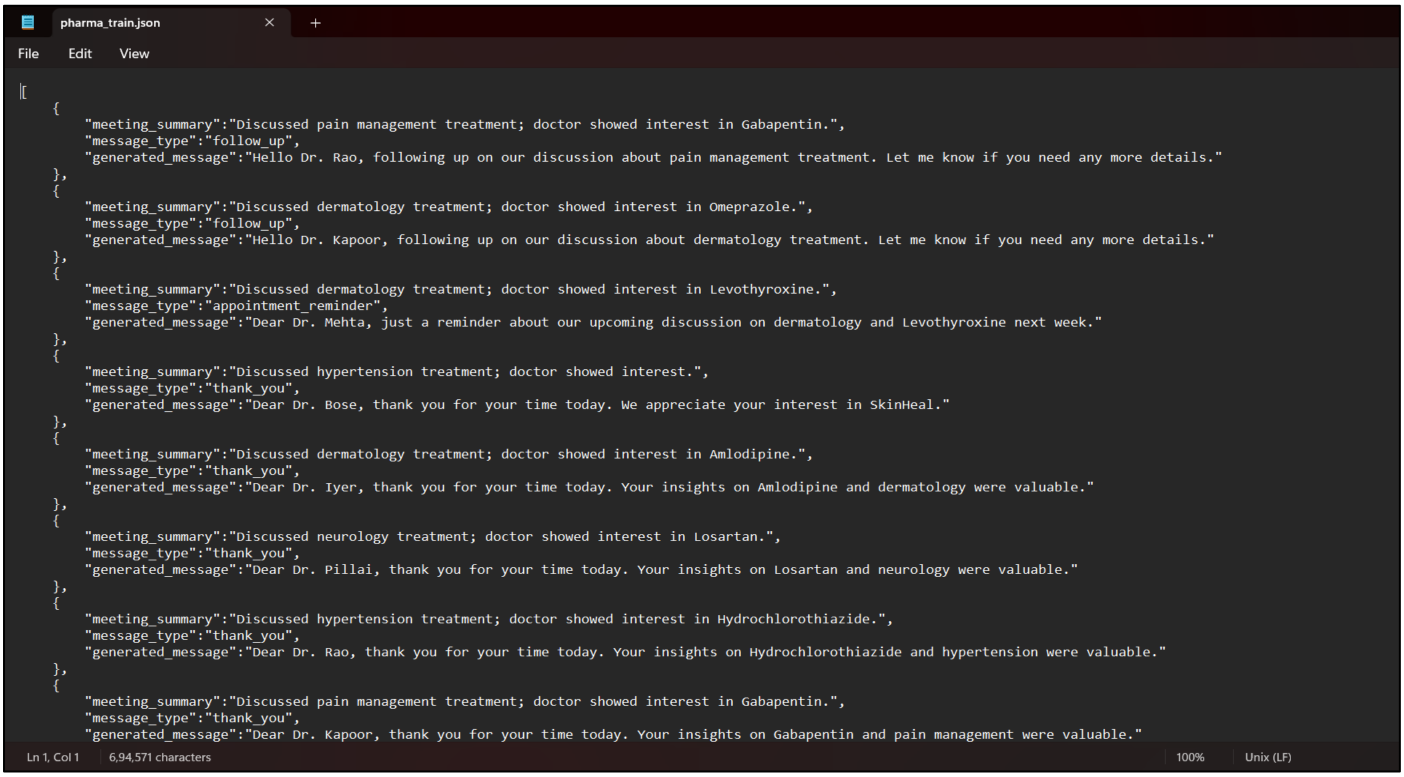
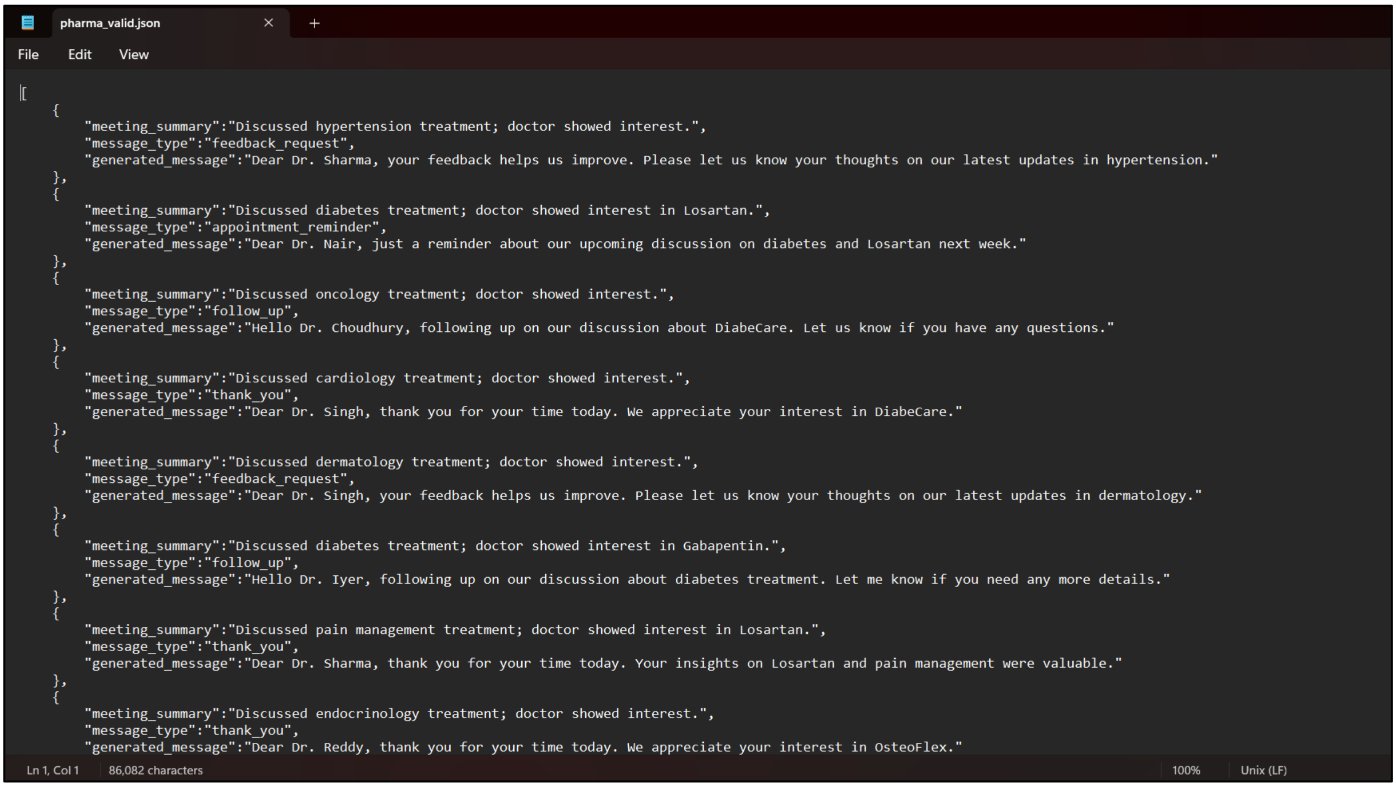
After completing this rigorous pre-processing stage, we organized the cleaned data into a final dataset of, around 47,000 messages in an Excel file finding a middle ground between data volume and computational feasibility [Fig.1] [8]. Given the large-scale nature of LLaMA 3 (8 billion) in 4-bit mode our aim was to achieve a dataset size that optimizes accuracy without compromising training efficiency. The final dataset took up 650 - 700 MB, in Excel form highlighted the need to convert it into a streamlined JSON format. We divided the JSON dataset into 3 sub-datasets in the ratio of 80:10:10 for Train:Valid:Test for perfect training of the model [Fig.2, 3, 4].



pharma_train.json
File Edit View
[
    {
        "meeting_summary":"Discussed pain management treatment; doctor showed interest in Gabapentin.",
        "message_type":"follow_up",
        "generated_message":"Hello Dr. Rao, following up on our discussion about pain management treatment. Let me know if you need any more details."
    },
    {
        "meeting_summary":"Discussed dermatology treatment; doctor showed interest in Omeprazole.",
        "message_type":"follow_up",
        "generated_message":"Hello Dr. Kapoor, following up on our discussion about dermatology treatment. Let me know if you need any more details."
    },
    {
        "meeting_summary":"Discussed dermatology treatment; doctor showed interest in Levothyroxine.",
        "message_type":"appointment_reminder",
        "generated_message":"Dear Dr. Mehta, just a reminder about our upcoming discussion on dermatology and Levothyroxine next week."
    },
    {
        "meeting_summary":"Discussed hypertension treatment; doctor showed interest.",
        "message_type":"thank_you",
        "generated_message":"Dear Dr. Bose, thank you for your time today. We appreciate your interest in SkinHeal."
    },
    {
        "meeting_summary":"Discussed dermatology treatment; doctor showed interest in Amlodipine.",
        "message_type":"thank_you",
        "generated_message":"Dear Dr. Iyer, thank you for your time today. Your insights on Amlodipine and dermatology were valuable."
    },
    {
        "meeting_summary":"Discussed neurology treatment; doctor showed interest in Losartan.",
        "message_type":"thank_you",
        "generated_message":"Dear Dr. Pillai, thank you for your time today. Your insights on Losartan and neurology were valuable."
    },
    {
        "meeting_summary":"Discussed hypertension treatment; doctor showed interest in Hydrochlorothiazide.",
        "message_type":"thank_you",
        "generated_message":"Dear Dr. Rao, thank you for your time today. Your insights on Hydrochlorothiazide and hypertension were valuable."
    },
    {
        "meeting_summary":"Discussed pain management treatment; doctor showed interest in Gabapentin.",
        "message_type":"thank_you",
        "generated_message":"Dear Dr. Kapoor, thank you for your time today. Your insights on Gabapentin and pain management were valuable."
Ln 1, Col 1 6,94,571 characters 100% Unix (LF)

Fig 2: Structured Train Dataset in JSON Format



pharma_valid.json
File Edit View
[
    {
        "meeting_summary":"Discussed hypertension treatment; doctor showed interest.",
        "message_type":"feedback_request",
        "generated_message":"Dear Dr. Sharma, your feedback helps us improve. Please let us know your thoughts on our latest updates in hypertension."
    },
    {
        "meeting_summary":"Discussed diabetes treatment; doctor showed interest in Losartan.",
        "message_type":"appointment_reminder",
        "generated_message":"Dear Dr. Nair, just a reminder about our upcoming discussion on diabetes and Losartan next week."
    },
    {
        "meeting_summary":"Discussed oncology treatment; doctor showed interest.",
        "message_type":"follow_up",
        "generated_message":"Hello Dr. Choudhury, following up on our discussion about DiabeCare. Let us know if you have any questions."
    },
    {
        "meeting_summary":"Discussed cardiology treatment; doctor showed interest.",
        "message_type":"thank_you",
        "generated_message":"Dear Dr. Singh, thank you for your time today. We appreciate your interest in DiabeCare."
    },
    {
        "meeting_summary":"Discussed dermatology treatment; doctor showed interest.",
        "message_type":"feedback_request",
        "generated_message":"Dear Dr. Singh, your feedback helps us improve. Please let us know your thoughts on our latest updates in dermatology."
    },
    {
        "meeting_summary":"Discussed diabetes treatment; doctor showed interest in Gabapentin.",
        "message_type":"follow_up",
        "generated_message":"Hello Dr. Iyer, following up on our discussion about diabetes treatment. Let me know if you need any more details."
    },
    {
        "meeting_summary":"Discussed pain management treatment; doctor showed interest in Losartan.",
        "message_type":"thank_you",
        "generated_message":"Dear Dr. Sharma, thank you for your time today. Your insights on Losartan and pain management were valuable."
    },
    {
        "meeting_summary":"Discussed endocrinology treatment; doctor showed interest.",
        "message_type":"thank_you",
        "generated_message":"Dear Dr. Reddy, thank you for your time today. We appreciate your interest in OsteoFlex."
Ln 1, Col 1 86,082 characters 100% Unix (LF)

Fig 3: Structured Valid Dataset in JSON Format

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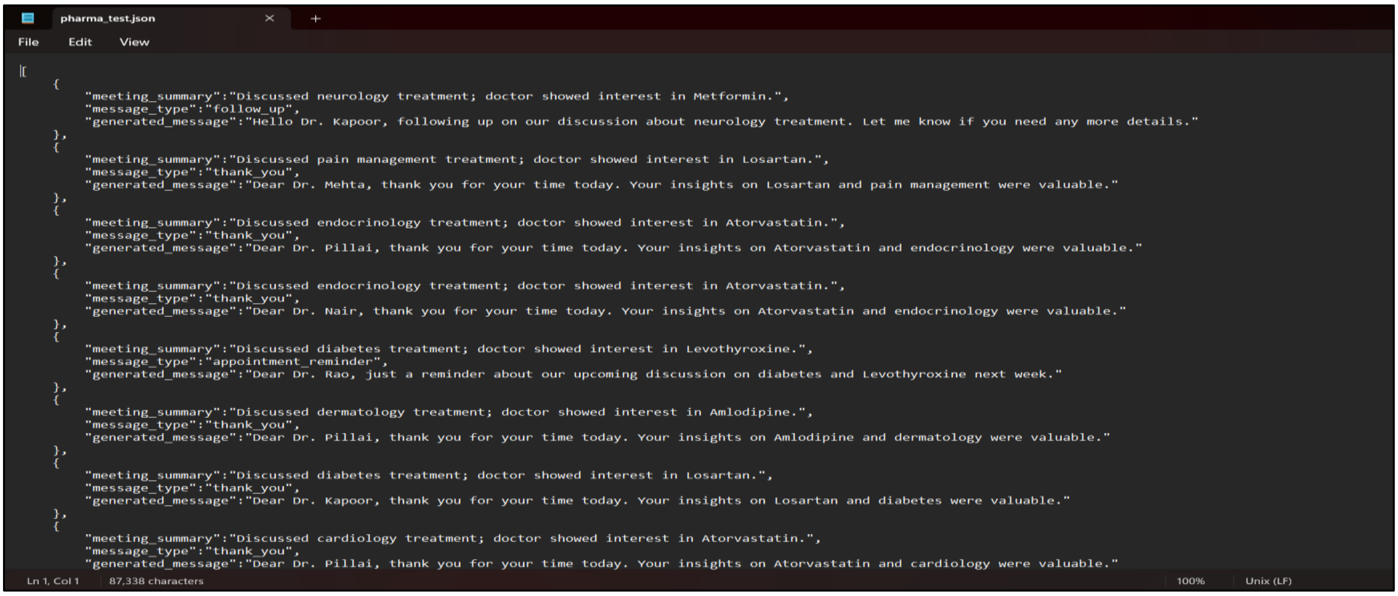


```
[
    {
        "meeting_summary":"Discussed neurology treatment; doctor showed interest in Metformin.",
        "message_type":"follow_up",
        "generated_message":"Hello Dr. Kapoor, following up on our discussion about neurology treatment. Let me know if you need any more details."
    },
    {
        "meeting_summary":"Discussed pain management treatment; doctor showed interest in Losartan.",
        "message_type":"thank_you",
        "generated_message":"Dear Dr. Mehta, thank you for your time today. Your insights on Losartan and pain management were valuable."
    },
    {
        "meeting_summary":"Discussed endocrinology treatment; doctor showed interest in Atorvastatin.",
        "message_type":"thank_you",
        "generated_message":"Dear Dr. Pillai, thank you for your time today. Your insights on Atorvastatin and endocrinology were valuable."
    },
    {
        "meeting_summary":"Discussed endocrinology treatment; doctor showed interest in Atorvastatin.",
        "message_type":"thank_you",
        "generated_message":"Dear Dr. Nair, thank you for your time today. Your insights on Atorvastatin and endocrinology were valuable."
    },
    {
        "meeting_summary":"Discussed diabetes treatment; doctor showed interest in Levothyroxine.",
        "message_type":"appointment_reminder",
        "generated_message":"Dear Dr. Rao, just a reminder about our upcoming discussion on diabetes and Levothyroxine next week."
    },
    {
        "meeting_summary":"Discussed dermatology treatment; doctor showed interest in Amlodipine.",
        "message_type":"thank_you",
        "generated_message":"Dear Dr. Pillai, thank you for your time today. Your insights on Amlodipine and dermatology were valuable."
    },
    {
        "meeting_summary":"Discussed diabetes treatment; doctor showed interest in Losartan.",
        "message_type":"thank_you",
        "generated_message":"Dear Dr. Kapoor, thank you for your time today. Your insights on Losartan and diabetes were valuable."
    },
    {
        "meeting_summary":"Discussed cardiology treatment; doctor showed interest in Atorvastatin.",
        "message_type":"thank_you",
        "generated_message":"Dear Dr. Pillai, thank you for your time today. Your insights on Atorvastatin and cardiology were valuable."
```


Fig 4: Structured Test Dataset in JSON Format

By using this format, we made sure that it works well with how Hugging Face handles tokenization and allows for training, with PyTorchs DataLoader feature in place [9]. The structured JSON format was chosen because it integrates natively with LLaMA 3's training architecture, reducing tokenization errors, and improving text coherence.

After getting the dataset ready, for use and proceeding to train the model we encountered difficulties due to the large size of LLaMA 3 (8B). However, integrating LoRA (Low-Rank Adaptation) with Hugging Face's PEFT framework introduced challenges in fine-tuning specific model layers while retaining pre-trained weights [10]. We had to use gradient checkpointing and dynamic learning rate scheduling due, to the demands to manage memory effectively and achieve stable convergence [11].

We trained the model for 40 epochs, given the dataset size and the computational intensity of fine-tuning an 8B parameter model. This number was selected to maximize learning without overfitting by using adaptive weight decay and evaluation-based early stopping mechanisms.

➢ *Key Libraries used for Training Process:*

- Hugging Face Transformers – Used for enhancing model fine tuning and seamless integration, with LLaMA 3 [12].
- PEFT (Parameter-Efficient Fine-Tuning) – Used for LoRA based adaptation to prevent excessive memory consumption [13].
- BitsAndBytes – To implement 4-bit quantization. Decrease the models resource usage, in BitsAndBytes software [14].
- PyTorch & Accelerate – For large-scale distributed training across GPUs [15].

Despite the intensive training requirements, our fine-tuned model demonstrated strongness in various validation measures, ensuring that the responses produced were coherent and, in line, with professional standards and regulations.

B. Phase 2: Dynamic Message Generation and Real-Time Integration

Once the model was fine-tuned accordingly to fit our needs precisely the following stage was to incorporate it into a live message creation system pipeline. Unlike traditional templating methods, our approach dynamically constructs responses without relying on predefined sentence structures. Of that the model examines sample inputs using Natural Language Understanding (NLU) and crafts personalized responses utilizing sentiment aware text generation methods [16].

➢ *Workflow Process:*

- Medical representative submits feedback – A medical representative shares feedback, by giving an overview of their interaction with the doctor.
- Natural Language Processing (NLP) techniques – The system identifies elements such, as entities related to health issues and emotional cues from the given input.
- Sentiment Analysis – Involves determining whether the feedback is positive or negative and makes sure that the response aligns with the doctor's sentiment.
- Dynamic Response Generation – The fine-tuned LLaMA 3 model generates a response by considering input, and its context.
- Multi-Channel Deployment – The generated message is formatted for Email or SMS or WhatsApp or any other based on client's method of communication [Fig.7, Fig.8, Fig.9, Fig.10].

To make sure everything works smoothly together we set up the model through an API based architecture, allowing the pharmaceutical companies to integrate the AI-powered messaging system into their existing applications, CRM tools, or web-based communication platforms. For testing purposes on how well, it works we used FastAPI to create an API that

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lets us check messages in time before rolling them out on a scale.

➢ *Future CRM and EHR Integration:*

In addition, to the phase of implementation plans mentioned earlier on ahead in the process development path lies the potential for future advancements which include linking up with Customer Relationship Management (CRM) software and Electronic Health Records (EHR). By integrating our AI model with platforms such as CRM, the pharmaceutical companies can track the doctor's historical interactions, and personalize follow-ups based on long-term behavioural understanding. Integration of EHR will improve messaging by aligning the responses with treatment histories, prescription data, and patient preferences, resulting in improved personalisation and interaction.

➢ *Summary and Transition to Results:*

In summary of our work, with the AI driven follow up messaging system; we utilize an algorithm called LLaMA 3 that has been customized using LoRA to create contextually appropriate responses for improved interaction between doctors and representatives. Our thorough preparation process before effective adjustments to the model allow. With a range of integration capabilities across platforms such as SMS or email services or WhatsApp or any other platform, we ensure customized engagement that aligns with each client preferences [Fig.5].

With the model being effectively trained and incorporated into a pipeline, in the real world setting the subsequent section will delve into examining the outcomes and assessing performance emphasizing enhancements, in message significance, precision and business effectiveness.

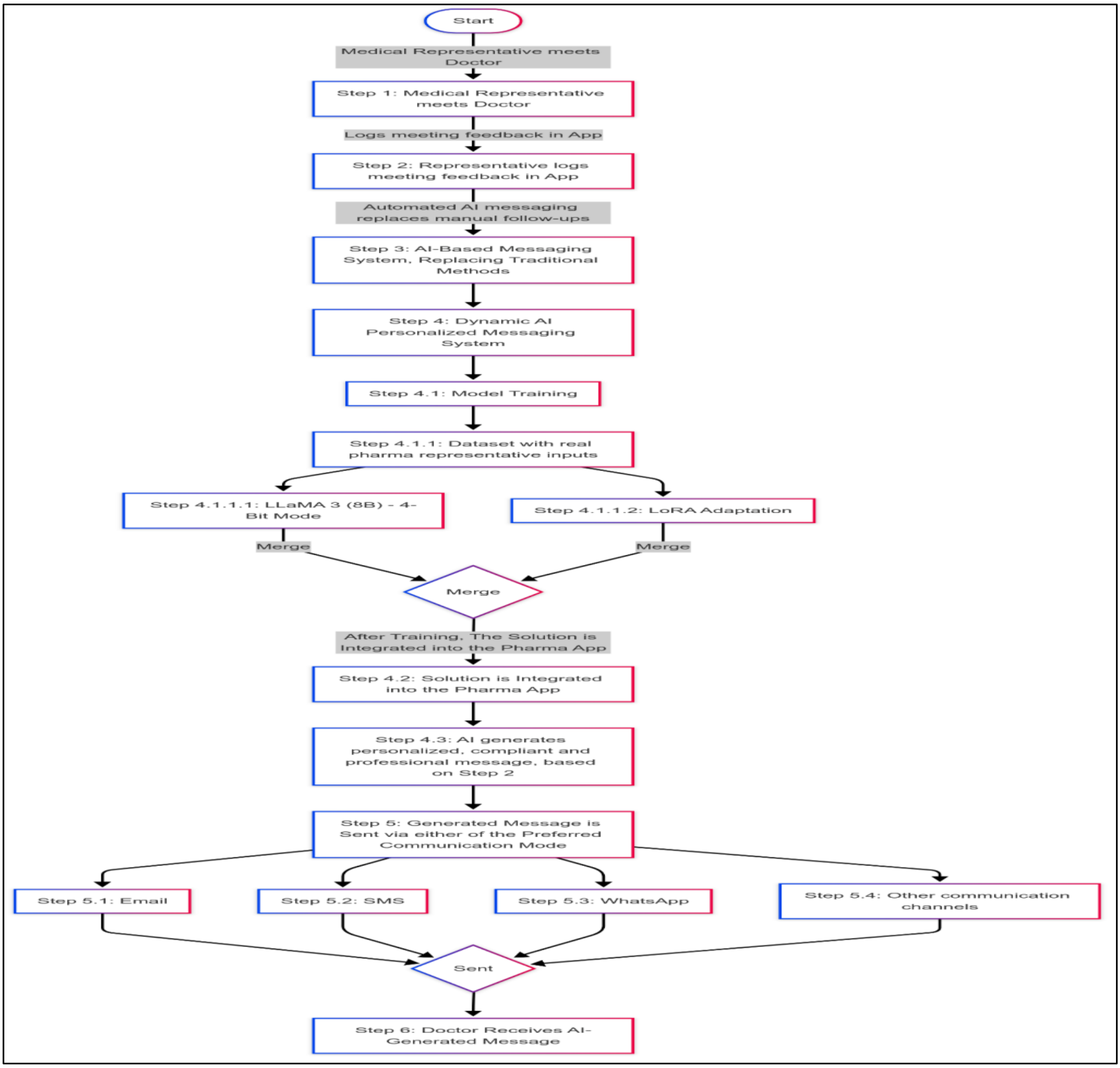

Fig 5: Flowchart of the Proposed Project

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III. RESULTS

A. Evaluation Metrics and Performance:

The use of post-visit messaging by doctors was assessed using different performance metrics to determine the accuracy, efficiency and appropriateness of the messages sent by the pharmaceutical representative and the type of message that each doctor preferred. The fine-tuned LLaMA 3 (8B) in 4-bit mode with LoRA integration produced very good results in the generation of textual information and ensured that the messages were relevant to the context as well as meeting the requirements of the industry. The evaluation was performed using standard NLP metrics; Loss, Perplexity, and BLEU Score to measure the quality of the language model's output and how close the output is to human output.

B. Loss and Perplexity Analysis:

One of the most important goals during training was to minimize the Loss value, which shows how well the model learned from the training dataset. The final training loss obtained was 0.0181884, and the benchmarks in the industry are usually set to achieve a loss score below 1.5 These results show that the model did a good job of minimizing prediction errors and was not overfitting to the training data [Fig.6]. The Perplexity Score, which is a measure of how ambiguous a model is with respect to a given text, was 1.0183548 which further supports the effectiveness of the model in generating reasonable and contextually fitting responses [Fig.6]. Lower perplexity values mean that the model is very confident in its outputs. Since the benchmarks for large language models in the industry are usually set to achieve a perplexity score below 5, the perplexity score that we got shows that the model is well trained for the task that it was developed to perform.

C. BLEU Score and Message Quality:

Additionally, the BLEU (Bilingual Evaluation Understudy) Score was used to determine how similar the texts that have been produced by AI are to those written by people. BLEU score is a popular metric in NLP that measures how similar the output text is to reference sentences with regard to the use of words, their order and meaning. Since the pharmaceutical industry is strict in its communication, it is crucial to ensure that the messages produced by AI are similar to those written by people. The BLEU score obtained was 0.92139877, which shows that the model is capable of producing messages that are coherent and professional as a human writer and at the same time and showing higher generation quality, the messages are pharma compliant as the highest benchmark range for BLEU score is 0.9 to 1 [Fig.6]. A higher BLEU score means that the AI can come up with responses that are not only coherent but also relevant to the given context, which is key in acquiring the trust and the attention of the pharmaceutical sales representatives and the doctors.

D. Accuracy and Business Impact:

The accuracy of the responses was measured through a comparison of the messages that were generated by AI and the messages that were written down by the pharma representatives. The model reached an estimated accuracy of 0.9589428, providing appropriate, orderly, and businesslike messages that are in line with the norms of the industry [Fig.6]. This high accuracy rate has proved that the model that was fine-tuned with the help of LLaMA 3 and LoRA is capable of comprehending the post-visit feedback and producing meaningful and well-organized messages. The model was able to preserve the contextual integrity and prevent hallucinations to some extent, which was a major achievement as no false, irrelevant, or misleading information was to be passed to the recipients.

Another interesting finding was the time efficiency in generating the messages in real-time. Once trained, the model was deployed using a lightweight and scalable API, that could easily be incorporated into the current communication channels of the pharmaceutical companies. The message response time was enhanced, making it possible to get the message across within a short time. The capability of designing the messages according to the feedback provided by the representatives and in real-time is very useful as it decreases the time spent on documentation and messaging following the visit. This automation ensures that the pharmaceutical representatives can spend more time in enhancing the doctor-patient relationships as they are not tied up in documentation and other related activities.

In addition, the model showed good generality when applied to different areas of pharmaceuticals and various communication styles, and therefore it can be easily applied to different companies. The use of LoRA for fine-tuning made it possible to adapt the model without having to retrain the model from scratch, thus making it easier to upgrade the model in the future and with minimal computational costs.

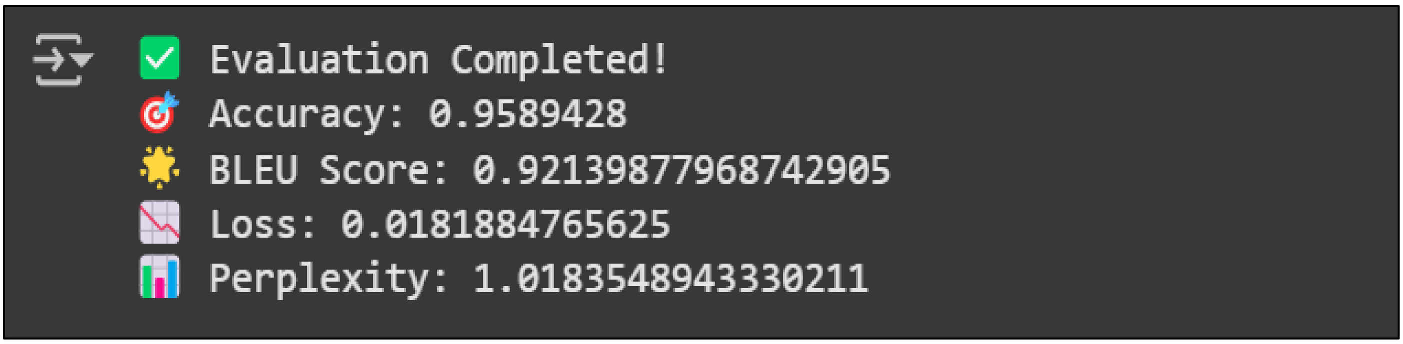

Fig 6: Evaluation Scores

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E. Scalability and Enhancements:

From the business impact perspective, the A.I. based messaging system could be useful for increasing the interaction, improving the communication processes and follow up. Doctors only get messages that are relevant to them and their practice, therefore reducing the chances of them feeling spammed and more likely to respond positively. The system guarantees that the follow-ups are only done, when necessary, thus avoiding sending frequent reminders while still keeping contact with healthcare professionals.

In conclusion, the findings show that the AI-based communication system achieves the goals of the project, that is, to automate, improve and optimize the post-visit communication between the pharmaceutical firms' representatives and doctors. The model validity is supported by the low loss, low perplexity, high BLEU score and high accuracy. Furthermore, the scalability and efficiency of the system make it a critical tool for pharma companies to ensure that the communication with doctors is frequent, on time, and relevant. With potential enhancements like integration with CRM and EHR, the system can develop into a fully automated AI communication solution.

These results provide a good basis for the discussion of the system in general and its implications in the next section, Conclusion and Future Prospects.

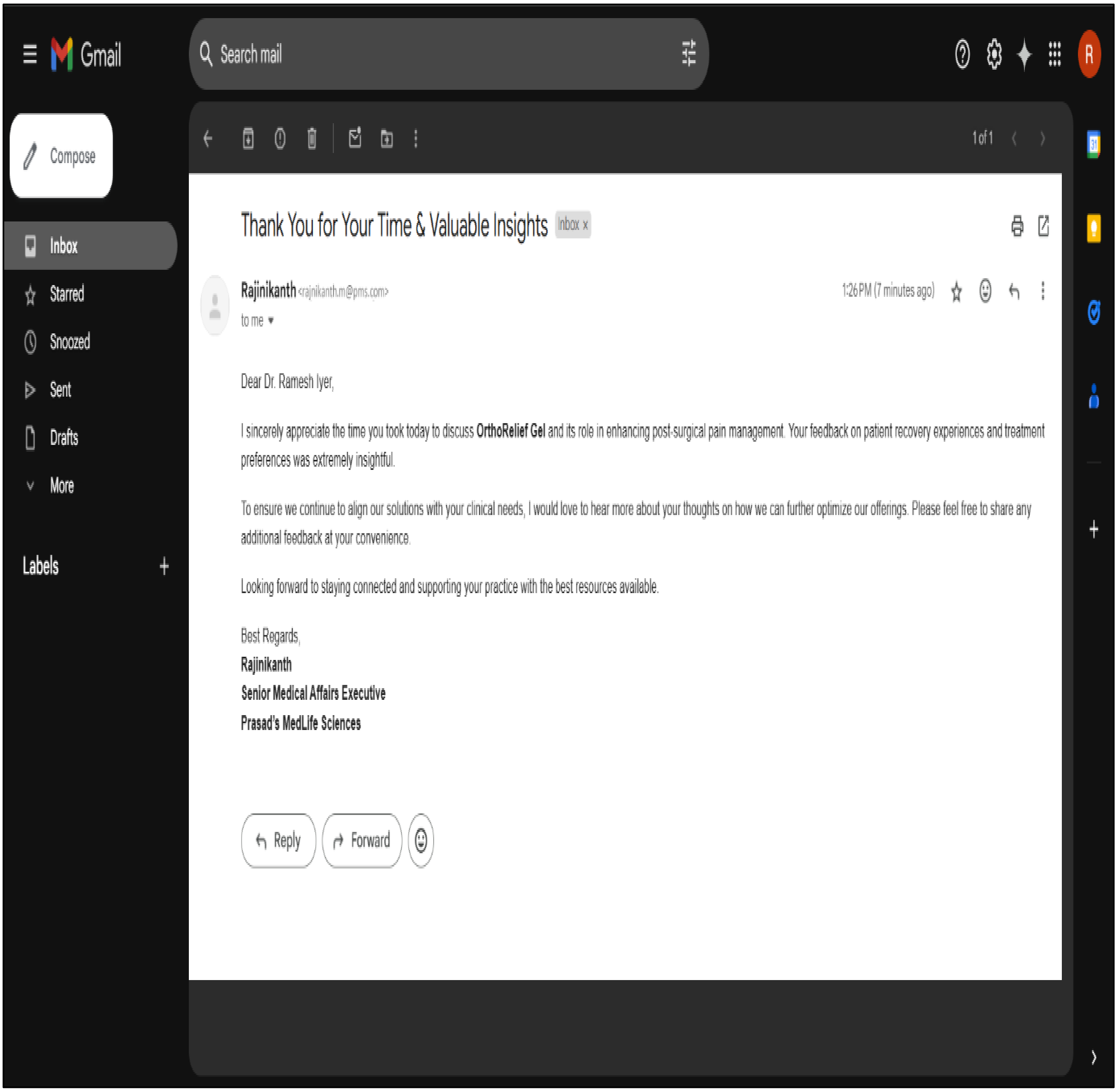

Fig 7: Generated Message Sent to Doctor's Mail

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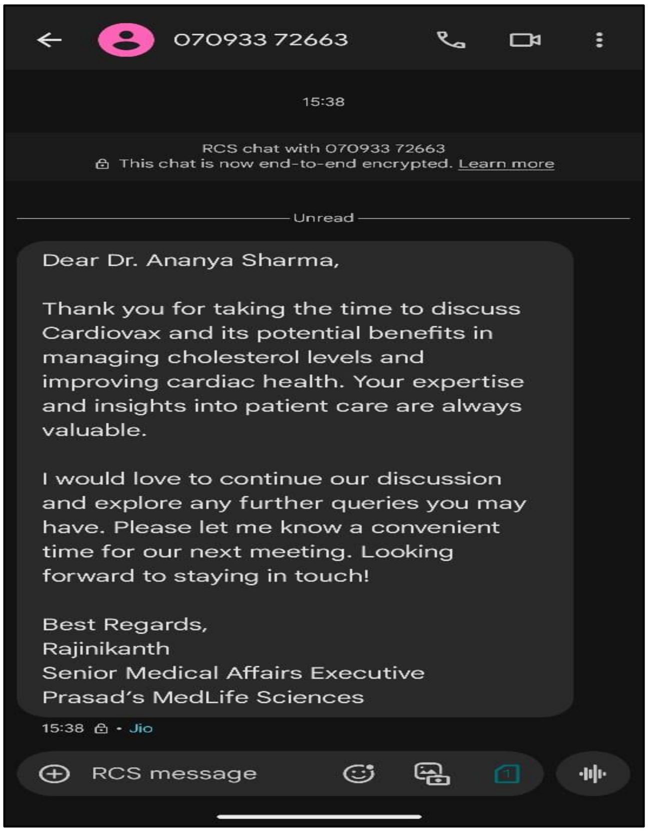

Fig 8: Generated Message Sent to Doctor's SMS

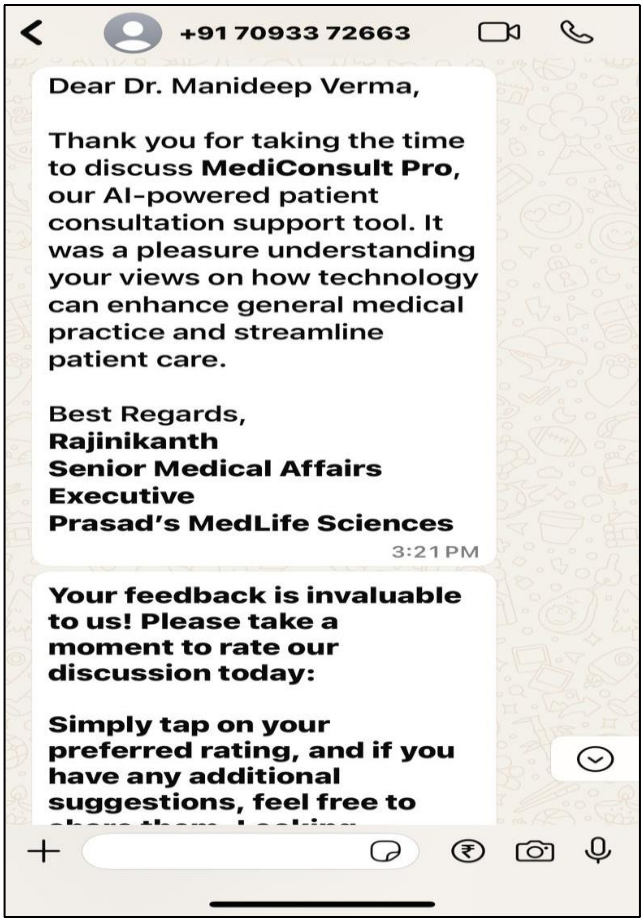

Fig 9: Generated Message 1, Sent to Doctor's WhatsApp

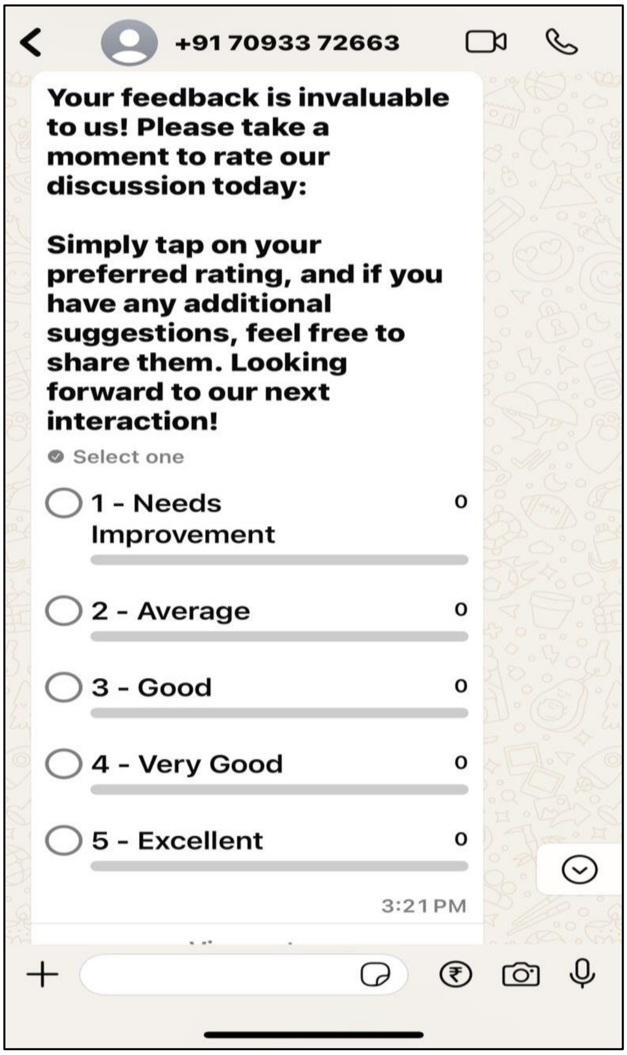

Fig 10: Generated Message 2, Sent to Doctor's WhatsApp

IV. CONCLUSION AND FUTURE PROSPECTS

A. Transforming Pharma Engagement with AI-Driven Automation

The outcomes of this project clearly show how the application of AI-driven automation can change the ways of the pharmaceutical engagement. Using LLaMA 3 (8B) in 4-bit mode with LoRA integration, we have been able to create a very efficient post-visit messaging system that will, improve communication, and foster better working relationships with doctors. The model was trained specifically for the task with high accuracy, using a structured dataset of real-world pharma feedback messages. The implementation of the NLP techniques such as the NLU and the sentiment analysis enabled the system to analyse and explain the messages in a simple and concise form to ensure that the communication is efficient, relevant and professional. The Loss and Perplexity scores were measured to prove that the model is capable of producing coherent and structured text with high accuracy, and the BLEU score was used to check the linguistic accuracy. Moreover, the API deployment makes it easy to integrate with the current communication channels to generate the message instantly with a small input from the pharmaceutical representative. All the processes, from training to deployment, were designed to make sure that the

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AI system is ready to work at its best, giving personal responses without sacrificing legal aspects. This system has proved to be a scalable and reliable solution for pharma companies trying to increase engagement while meeting the necessary requirements through the process of eliminating the inconsistencies of manual messaging and reducing the administrative workload.

B. Expanding Capabilities: Future Integrations with CRM and EHR

There are many potential applications of this technology in the future that are unlike the current application. Another of the most important potential applications of the system is its integration with Customer Relationship Management (CRM) systems and Electronic Health Record (EHR) systems. It would be possible to track all the interactions with the doctors fully if the model was integrated into the CRM tool. It would help the representatives know the historical engagement details, preferences, and communication patterns of the doctors. This could further enhance message personalization as it would be possible to tailor the message to match the specific interests, preferences, and areas of interest of a doctor. Furthermore, through the use of EHR one could make communication more data driven and thus the pharmaceutical representatives would be in a position to discuss patient's treatment plans, prescriptions given to the patient and recent medical research while ensuring that the data processing is done in a way that is consistent with the regulatory requirements. The next level of integration would allow the pharmaceutical companies to move from purely reactive communication to proactive AI-powered engagement where the representatives have real-time data to share message that will be relevant to the doctor and their practice. Some of the future enhancements may also entail the support for multiple languages in order to expand the outreach to the global market for the pharma firms which operate in different regions with different languages. Moreover, the ability to incorporate predictive analytics into the current AI model could enable the system to determine the possible informational needs of the doctors, recommend relevant scientific literature, and even suggest the most appropriate times to follow up, thus ensuring that the engagement process is more deliberate and data influenced.

C. Redefining Industry Standards: The Business Impact of AI-Powered Messaging

From a business point of view, this AI-powered messaging system has a great potential. The pharmaceutical industry is a very competitive one and the companies involved have to find new and better ways of engaging their targets and standing out from the crowd. This automated messaging solution not only streamlines communication but also helps make pharma firms the leaders in using AI for engagement. The capacity to send personalized, on-time, and informative messages is a way of ensuring that the companies are always in the minds of the doctors, increasing the brand awareness and credibility. Through the automation of routine tasks, pharma representatives can spend more time on the development of relationships and meaningful conversations that may result in better interactions and sales. It also means that the system dictates that there should be no chance of a follow-up without it being acted on, thus increasing the conversion rates of conversations to prescriptions. Also, the lack of generic and generic messaging means that the doctors are only getting the information that is most relevant and useful to them, thus increasing the chances of their response and participation. This model is scalable in the long run, which means that as companies grow, the AI can grow with them to handle more interactions, new medical topics, and industry standards. Through the application of new AI technologies, the pharmaceutical companies are well placed to transform the way physicians are being reached, increase the effectiveness of the process and, therefore, offer better patient care through more frequent and timely communication. It is no longer a question of being able to send the right message to the right doctor at the right time, but of being able to do so in a way that will significantly contribute to the growth of business and revolutionize the entire industry.

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