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APPLIED RESEARCH

QueryMintAI: Multipurpose Multimodal Large Language Models for Personal Data

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ABSTRACT QueryMintAI, a versatile multimodal Language Learning Model (LLM) designed to address the complex challenges associated with processing various types of user inputs and generating corresponding outputs across different modalities. The proliferation of diverse data formats, including text, images, videos, documents, URLs, and audio recordings, necessitates an intelligent system capable of understanding and responding to user queries effectively. Existing models often exhibit limitations in handling multimodal inputs and generating coherent outputs across different modalities. The proposed QueryMintAI framework leverages state-of-the-art language models such as GPT-3.5 Turbo, DALL-E-2, TTS-1 and Whisper v2 among others, to enable seamless interaction with users across multiple modalities. By integrating advanced natural language processing (NLP) techniques with domain-specific models, QueryMintAI offers a comprehensive solution for text-to-text, text-to-image, text-to-video, and text-to-audio conversions. Additionally, the system supports document processing, URL analysis, image description, video summarization, audio transcription, and database querying, catering to diverse user needs and preferences. The proposed model addresses several limitations observed in existing approaches, including restricted modality support, lack of adaptability to various data formats, and limited response generation capabilities. QueryMintAI overcomes these challenges by employing a combination of advanced NLP algorithms, deep learning architectures, and multimodal fusion techniques.

INDEX TERMS Multimodal large language models, generative AI, private database, Langchain, OpenAI.

I. INTRODUCTION

The need for intelligent systems that can process and comprehend many types of data is growing quickly in the age of digital transformation. In order to meet this need, multimodal language models, or LLMs, have become extremely effective instruments. They allow for fluid communication with a wide range of data formats, including text, photos, videos, audio, and documents. Nevertheless, current LLMs frequently face challenges in effectively managing numerous activities, deriving significant insights from intricate data, and delivering smooth and consistent replies across various modalities. In an effort to address these issues, this study presents QueryMintAI, a feature-rich multimodal LLM designed for handling personal data in a variety of contexts and media. The efficient handling of diverse data inputs, including text, photos, videos, audio, and documents, while generating outputs that are coherent and contextually appropriate, is a problem that many existing LLMs frequently encounter. These restrictions impede the creation of adaptable and intuitive AI systems that can communicate with people in a variety of ways. Furthermore, the usability and efficacy of current models are further complicated by the lack of integration across various data kinds and tasks, which results in less-than-ideal user experiences and restricted application in real-world scenarios. Existing LLMs have shortcomings in a number of important areas. First of all, because most models are created for particular uses cases or modalities, they provide disjointed solutions that are ill-suited to deal with a variety of data sources. Furthermore, many models exhibit difficulties with resilience, scalability, and performance when faced with intricate data structures or

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huge datasets. Furthermore, there are a number of obstacles that make it difficult to use current LLMs in practical settings, including interpretability limitations, domain-specific knowledge shortages, and linguistic biases.

The need for improved LLMs that can seamlessly incorporate text, images, videos, audio, and documents is highlighted by the growing demand for AI-driven systems that can analyze and comprehend personal data across numerous modalities. QueryMintAI seeks to transform the way consumers interact with AI systems by solving the shortcomings of current models and providing a unified solution for multimodal data processing. This will enable intuitive and tailored experiences across a wide range of tasks and disciplines. QueryMintAI is a multimodal LLM that can process a wide range of data inputs, such as text, photos, videos, audio, and documents, and produce text, images, videos, and audio that makes sense in the context. The model makes use of cutting-edge methods in computer vision, audio processing, and natural language processing to facilitate smooth user interaction across a variety of modalities. QueryMintAI provides a comprehensive solution for processing personal data and enabling natural language communication between users and AI systems thanks to its integrated design and advanced algorithms. When it comes to current LLMs, QueryMintAI has a number of clear benefits. First off, its multimodal architecture makes it possible to seamlessly integrate diverse data input and output formats, providing flexible and intuitive interactions across a range of modalities. To handle intricate data structures, QueryMintAI also includes sophisticated algorithms that guarantee scalability, performance, and resilience in practical situations. Additionally, the model tackles problems like interpretability limitations, domain-specific knowledge gaps, and linguistic biases, which improves the usefulness and efficacy of AI-driven solutions in a variety of contexts and applications. QueryMintAI is innovative in that it takes a comprehensive approach to multimodal data processing, combining the most recent methods from computer vision, audio processing, and natural language processing into one cohesive system. QueryMintAI provides a revolutionary method for processing personal data across many modalities by combining sophisticated algorithms with a flexible architecture, allowing users and AI systems to communicate in a personalized and intuitive manner. Furthermore, the model's emphasis on resolving the shortcomings of current LLMs and providing a unified solution for multimodal data processing marks a noteworthy development in the area of AI-driven communication and personal data management. The main contributions of this paper are:

- A breakthrough development in linguistic and multimodal AI systems, QueryMintAI provides a complete solution for managing a variety of jobs and data types while putting user privacy first. QueryMintAI enables users to interact with the system in a seamless manner by integrating state-of-the-art language models such as GPT-3.5 Turbo, DALL-E-2, Whisper v2-large, and TTS-1. Users can input text, images, videos, documents, URLs, audio recordings, and SQL databases, and receive outputs in a variety of formats, including text, image, video, and audio.
- With its multimodal approach, QueryMintAI can generate textual responses as well as realistic visuals, dynamic videos, and audio. This allows it to meet a broad range of user needs. The system's sophisticated natural language production and interpretation capabilities guarantee consistent and contextually appropriate outputs across many modalities, improving the user experience as a whole.
- One of QueryMintAI's unique selling points is its user-centric design, which includes an easy-to-use Streamlit web application interface. Usability is given top priority in this design decision, making it simple and effective for users to interact with the system.
- QueryMintAI offers improved privacy protections, setting it apart from other monomodal and multimodal AI apps. Users can enter their personal information with confidence because QueryMintAI has strong security safeguards in place to protect it and lessen the possibility of data breaches or leaks.

This research paper's remaining section is structured as follows: Section II: Related Works provides background information on IR, various LLM kinds, quick engineering, and Langchain. The suggested model's complete architecture, fine tuning, model description, and application workflow are presented in Section III: Methodologies along with an evaluation of the model. Section IV displays the application's results, including the comparative analysis with other models and the user's interaction with the program and the reply from QueryMintAI. Section V explores some possible future directions, and we wrap up the research by summarizing the main conclusions.

II. LITERATURE REVIEW

A. MACHINE LEARNING, DEEP LEARNING AND NLP MODELS

Previous research outlines an iterative process for improving systematic literature reviews (SLRs) that combines machine learning and text mining. Its main goals are to help with document screening, classify abstracts, and suggest better search terms. This method, which is especially helpful for broad or ambiguous search topics, strikes a compromise between automated processing and researcher judgment [31]. A prior study presents a deep feature weighting strategy that is distinct to a class for Multinomial Naïve Bayes (MNB) text classifiers. This method increases the accuracy of classification by giving each class its own weight and using it to inform conditional probability estimations. The method's higher performance and efficiency over existing approaches are demonstrated by experiments conducted on 19 datasets [32]. A hybrid feature selection method that combines SVM-RFE and TF-IDF is presented in a previous work for sentiment classification. Experiments conducted using Sentiment Labelled and IMDB datasets demonstrate that the strategy outperforms previous approaches in terms

of feature reduction and excellent classification accuracy. Performance in classification is maintained while optimizing computational resources [33]. The models were compared for BBC news text categorization using Random Forest, K-Nearest Neighbors (KNN), and Logistic Regression. The models were assessed based on F1-score, accuracy, precision, and confusion matrix. With precision values of 94% for business, 100% for entertainment, 97% for politics, 99% for sports, and 98% for technology, Logistic Regression produced 97% accuracy and F1-score. While demonstrating strong performance, Random Forest and KNN fell short of Logistic Regression across the board [34]. Prior research contrasts deep learning and Random Forests (RFs) for classifying legal texts. Using the top 400 domain ideas, the RFs model outperformed deep learning techniques that rely on pre-trained embeddings, achieving high F1 scores (up to 99%) across 50 categories. The study emphasizes the efficiency and efficacy of RFs, especially for US legal texts [35]. Through the resolution of cut-off distance and cluster density variations, the DPC-MC method improves Density Peaks Clustering. It incorporates micro cluster binding for complicated forms, uses a self-recommendation technique to include lower-density clusters, and estimates density using k-nearest neighbors. Studies reveal that DPC-MC performs better than current techniques in a number of criteria [36].

An earlier study examines vector embeddings of relational structures and graphs, with an emphasis on their theoretical foundations. In addition to reviewing useful methods like word2vec, node2vec, and graph2vec, it presents theoretical strategies based on homomorphism vectors and the Weisfeiler-Leman algorithm. These frameworks provide insights into embedding quality and complexity, with the goal of bridging the gap between discrete data and differentiable machine learning. The study emphasizes the need for more investigation, particularly in the areas of querying embedded data and extending embeddings to higher-arity relations [37]. An earlier study presents a hybrid Bi-LSTM+CNN text categorization model with an attention mechanism. It performs better than CNN, LSTM, and MLP models when tested on the IMDB dataset, attaining an accuracy of 0.9141 and an F1 score of 0.9018. The model improves classification performance by effectively addressing long-term dependency and data-loss concerns [38]. An improved Long Short-Term Memory (LSTM) Recurrent Neural Network (RNN) model for Automatic Speech Recognition (ASR) is presented in a previous study. As a forget gate inside the LSTM, it integrates an RNN to enhance continuous input stream processing. The model outperformed other deep learning models, achieving 100% validation accuracy and 99.36% accuracy [39]. In order to improve coherence and diversity in autonomous sentence production, deep learning techniques such as RNNs, LSTMs, and GRUs are essential. By addressing the vanishing gradient issue with RNNs, LSTMs and GRUs enhance long-term dependency learning. Large-scale datasets are used to train deep learning models, which help with tasks like text generation, translation, and chatbot answers. Perplexity metrics are used to assess the models' performance [40]. A previous study addresses the difficulties in producing text with long-term dependencies by presenting a Sepedi text generation model that makes use of Long Short-Term Memory (LSTM) networks. The model, which was trained on the NCHLT Sepedi corpus, demonstrated the potential of LSTMs in producing coherent Sepedi text sequences by achieving 50.3% accuracy with little data and 20 epochs [41]. A prior study presents a sentiment analysis text classification method with Gated Recurrent Units (GRUs) that achieves 87% accuracy on a dataset of movie reviews. By identifying long-term dependencies, the GRU model solves the vanishing gradient issue and outperforms conventional Recurrent Neural Networks (RNNs). Improved sentiment categorization and efficient processing of sequential data are two important improvements [42].

For text categorization, a previous study suggests using FastText word embeddings to improve a Convolutional Neural Network (CNN) model. The model performs well on evaluation across seven datasets; noteworthy performance includes 96% on AG News and 95% on Yelp Reviews Polarity. It shows efficiency with just three CNN layers and surpasses current approaches in accuracy, precision, and recall [43]. Weaknesses in sequence-to-sequence (Seq2Seq) models for chatbot natural answer creation are covered in a previous review. It points up problems like exposure bias and generic responses and suggests improvements like more encoders, embeddings, and multi-task learning. Despite adding complexity, these enhancements are intended to overcome model limitations and produce more insightful results [44]. An earlier study looks at utilizing TensorFlow 2 to create practical NLP applications. It provides useful insights for creating efficient NLP solutions by covering sophisticated approaches including Named Entity Recognition (NER), Recurrent Neural Networks (RNNs), sequence-to-sequence models, and Transformers [45]. A recent study presents a neural machine translation (NMT) model called GRU-gated attention model (GAtt), which improves context vector classification by fine-tuning source representations using prior decoder states. Studies reveal that GAtt considerably raises BLEU scores—35.92 on Chinese-English and 23.42 on English-German—beyonding conventional techniques and successfully resolving over translation concerns [46]. Building GPT requires attention models because they allow the model to concentrate on pertinent portions of the input, effectively managing long-range dependencies. Attention processes improve comprehension of context and sequence by assigning various weights to distinct input components, which increases the capacity of GPT models to produce text that is coherent and contextually accurate [47]. Advances in Transformer-based Pre-trained Language Models (PLMs) for Controllable Text Generation (CTG) have been made recently. Giving scholars and practitioners in the field of Natural Language Generation (NLG)

a thorough overview, it divides approaches into categories such as fine-tuning, retraining, and post-processing, assesses methodologies, and talks about obstacles and potential future directions [48].

B. LARGE LANGUAGE MODELS

Scientific literature has drawn attention to research artifact analysis (RAA) as a critical component of knowledge discovery in recent years. To improve research reproducibility and transparency, numerous attempts have been undertaken to create databases for recognizing and categorizing research artifacts (RAs), including software and datasets [4]. Conventional methods frequently ignore unidentified and unrecorded resources in favor of named research assistants (RAs). This gap drives the creation of new approaches to overcome these issues and boost RAA's efficacy, like utilizing human-in-the-loop processes and fine-tuning large language models (LLMs) with methods like Low-Rank Adaptation (LoRA). We are tracking the development of information retrieval (IR) systems, following their path from conventional term-based techniques to cutting-edge neural models like ChatGPT and GPT-4, which are revolutionizing natural language processing and finding new applications in IR systems [1]. There have been talks on how LLMs can improve IR effectiveness, but they also come with hurdles, such as interpretability problems and a lack of data. Promising avenues for further research are presented by recent developments in query rewriters, retrievers, re-rankers, and readers in the context of LLM integration.

Large Language Models (LLMs) can be improved in terms of performance, flexibility, and moral behavior by fine-tuning or refining them. Techniques for fine-tuning aim to adapt LLM behavior to particular work needs or ethical norms. Examples of this include aligning replies with human preferences and fine-tuning with manually created datasets [3]. To improve the model's comprehension of longer texts, strategies like expanding the context window make use of efficient attention mechanisms and position interpolation. With retrieval-augmented LLMs retrieving relevant information for more accurate responses and tool-augmented LLMs facilitating engagement with external resources to complete tasks, augmented LLM [3] techniques use external memory or tools to augment model capabilities. Together, these tactics help to continuously improve and optimize LLMs for a variety of scenarios and applications, addressing issues with performance, adaptability, and moral considerations in tasks involving natural language processing. Large Language Models (LLMs) are cognitive controllers for autonomous agents that play a key role in reasoning, planning, and memory assimilation, according to recent studies. It highlights how to improve agent performance through techniques like prompting and feedback mechanisms, highlighting how flexible LLMs are in changing situations. They examine the use of LLMs in a variety of contexts, including physical activities like navigation and manipulation as well as multi-agent systems. It also discusses parameter-efficient fine-tuning, quantization, and pruning strategies for optimizing LLMs for efficiency.

An earlier study fills a vacuum in the field by presenting a method for knowledge distillation (KD) in large language models (LLMs), where KD approaches have mostly concentrated on classification models or small LLMs mimicking black-box APIs. The paper enhances white-box KD for LLMs by proposing reverse Kullback-Leibler divergence (KLD) [5] as the objective function and introducing optimization tactics such as teacher-mixed sampling and single-step decomposition. Scalable model compression strategies benefit from the suggested method, called MINILLM, since empirical evaluations show that it is helpful in producing accurate replies with greater quality, less exposure bias, and better calibration when compared to baselines. One challenge is that false contexts can trick large language models (LLMs), causing generated text to contain hallucinations. In order to protect LLMs from false information, it presents Truth-Aware Context Selection (TACS) [6], a technique that filters input context according to its veracity. To create an attention mask, TACS uses fine-grained truth detection, keeping the true context and eliminating the false. The outcomes of the experiment indicate noteworthy enhancements in the quality of responses from LLMs, confirming the efficacy of TACS in reducing the adverse effects of false information. In order to assess LLMs' resistance to context interference, the study also presents the Disturbance Adaptation Rate, which offers valuable information on how to continue producing genuine writing in the face of outside influences.

C. PROMPT ENGINEERING

AI prompt engineering has had a revolutionary effect on how organizations operate and communicate. The AI revolution, the rise of in-context learning through prompting, and the significant impact of generative AI technologies such as ChatGPT across multiple domains have all been facilitated by unsupervised learning and the transformer architecture [2]. With the rise of AI prompt engineering, creating good prompts requires a great deal of understanding of context, feedback, and clear instructions. It also has the potential to affect future labor markets.

D. MONOMODAL AND MULTIMODAL LLMS

A thorough review of text categorization methods has been conducted, with an emphasis on the most recent developments made possible by transformer-based models, in particular large language models (LLMs). Through the use of methodology that combine conventional research procedures with NLP-facilitated approaches like co-citation and bibliographic coupling, they explore a range of applications, from sentiment analysis to question answering. Their review offers a more comprehensive taxonomy of text categorization applications that takes into account inputs that are unimodal as well as multimodal [7]. They assess how transformer-based

models have changed over time, as well as their cost, safety, and accuracy in a variety of datasets and applications. A study on generative AI text categorization using ensemble methods and large language models (LLMs) is presented in an earlier publication [8]. The main goals were to differentiate text produced by AI from text written by humans and to assign particular language models to the created material. To accomplish this aim, the study investigated different pre-trained LLMs and conventional machine learning classifiers. The suggested ensemble strategy was found to be beneficial based on experimental data, which showed competitive performance in binary and multiclass classification tasks in both Spanish and English. The method exhibits potential in precisely recognizing AI-generated content and pinpointing the source LLM that produced it. The effectiveness of fine-tuning Large Language Models (LLMs) like DistilBERT [9] for domain-specific tasks like text classification in legal documents has been highlighted by recent studies. The performance of pretrained and fine-tuned LLMs was compared through tests using the DistilBERT model from Hugging Face. The outcomes show that fine-tuning increases the model's comprehension of domain-specific language, which boosts predictions. This emphasizes how important domain adaptation is to the best LLM optimization for particular tasks, especially in the legal domain where complex language is common. Outperforming other approaches like AudioLDM, the previously proposed TANGO [10] model generates text-to-audio (TTA) using an instruction-tuned Large Language Model (LLM), FLAN-T5. TANGO produces state-of-the-art results on objective metrics like as Frechet Audio Distance (FAD) and subjective assessments of audio quality and relevance to input text by employing a latent diffusion model (LDM) guided by FLAN-T5. Because FLAN-T5 is a powerful text encoder, even if TANGO is only trained on the AudioCaps dataset, it outperforms models trained on larger datasets, demonstrating its efficacy and efficiency in TTA creation.

Using natural language supervision, the CLIP (Contrastive Language-picture Pre-training) model [11] acquires strong picture representations. Without requiring task-specific training, it achieves amazing performance across multiple datasets, substantially advancing zero-shot transfer learning in computer vision. CLIP demonstrates its resilience and versatility in interpreting visual concepts from text, outperforming previous approaches such as Visual N-Grams. State-of-the-art findings are made possible by its creative methodology, effective pre-training, and scalable dataset construction. This represents a major advancement in the learning of transferable visual models directly from natural language supervision. Specifically, DiffusionGPT [12] builds on the ChatGPT model by leveraging the text-davinci-003 version. This model is the main large language model (LLM) controller for DiffusionGPT and is available via the OpenAI API. DiffusionGPT uses Large Language Models (LLMs) to present a revolutionary text-to-image creation method. It overcomes the drawbacks of current models by providing a unified framework that can integrate domain-specific models and handle a variety of input modalities. DiffusionGPT shows promise for improving picture synthesis as it performs better than conventional stable diffusion models. A wide variety of models were chosen by DiffusionGPT from the Hugging Face and Civitai communities. It analyzes and extracts pertinent data from input prompts—prompt-based, instruction-based, inspiration-based, and hypothesis-based—using the LLM. It makes effective model selection possible by arranging generative models according to their properties into a hierarchical tree structure.

For SQL-to-text [14] creation, the Falcon-7B-Instruct model—a Large Language Model (LLM)—was used. Falcon-7B-Instruct is a causal decoder-only model with an architecture optimized for inference with FlashAttention and multiquery, that has been refined on a large dataset. Exact instructions or assistance are given to this model throughout the text generating process. The Falcon-7B-Instruct model was used in a zero-shot setting, which means that without fine-tuning for particular SQL-to-text datasets, it predicted query explanations given unknown SQL queries. On the Spider and WikiSQL datasets, the Falcon-7B-Instruct model outperformed other models, including T5 and Graph2Seq, in terms of accuracy rates. A innovative method for text-to-image generation is suggested by LayoutLLM-T2I [13], which uses Large Language Models (LLMs) to develop layouts automatically and without human assistance. It uses fine-grained object-interaction diffusion for high-faithfulness picture synthesis and uses in-context learning to activate LLMs for layout generation. LayoutLLM-T2I outperforms previous models in addressing misalignment problems in intricate scenarios and improves semantic alignment between output images and written prompts. Extensive studies demonstrate the improved performance of the model, which blends spatial and semantic relation knowledge, numerical reasoning, and sophisticated layout planning.

A previously proposed MultiModal Large Language Model (MM-LLM) uses ImageBind for unified encoding in conjunction with several modality encoders for inputs, such as NFNet-F6, ViT, CLIP ViT for visuals, C-Former, HuBERT, BEATs for audio, and ULIP-2 with Point-BERT for 3D data [15]. It performs tasks including audio synthesis, video captioning, and image-text generation by integrating Modality Generator, LLM Backbone, Input/Output Projectors, and Modality Encoder. It exhibits high-level thinking and decision making in several modalities with exceptional performance and efficiency. This is made possible by an improved training pipeline that includes MM Pre-Training and MM Instruction-Training phases, which improves human interaction and zero-shot capabilities. WHISPER-BASE for audio, LLAMA-7B for textual encoding, and CLIP-ViT-B/16 for visual encoding are all integrated in the MACAW-LLM [16] model. Through multi-head self-attention techniques, its alignment module harmonizes

multi-modal features, enabling efficient integration. By using one-step fine-tuning, MACAW-LLM reduces error propagation and simplifies adaptation in comparison to earlier models. The modality, alignment, and cognitive modules of the MACAW-LLM model allow for the integration of textual, audio, and visual information. Using multi-head self-attention processes, it efficiently aligns representations from many modalities, enabling smooth integration for a variety of tasks. Its one-step instruction fine-tuning reduces mistake propagation and makes adaption easier. Multi-modal LLM research is supported by the MACAW-LLM instruction dataset, which includes a variety of instructional activities.

A probabilistic graphical model framework that integrates both audio and visual modalities is usually part of BLIVA (Bayesian Latent Variable Models for Audiovisual Data) [17]. The study employed Bayesian methods to estimate parameters, quantify uncertainty, and incorporate hidden variables to identify underlying structures and correlations in the data. Mel-frequency cepstral coefficients, or spectrograms, are modules that are used to extract information from audio recordings. Latent variables in the audiovisual data were modeled using Gaussian Mixture Models (GMMs) and Hidden Markov Models (HMMs), along with their respective relationships. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two examples of deep learning architectures that BLIVA used to learn intricate mappings across modalities and extract information from audio and visual input streams. A multimodal LLM called ChartLlama [18] presents a technique for creating datasets that uses GPT-4 for instruction tailoring. In ChartQA, Chart-to-text, and Chart-extraction tasks, it performs better than previous models. Data synthesis from pre-existing datasets and data generation from scratch are included in methodology. Through the integration of massive language models from Vicuna with multimodal encoders from ImageBind, PandaGPT [19] enables complex instruction-following tasks in both the visual and auditory realms. Aligned image-text pairs are used for training, with the goals of aligning feature spaces and reducing trainable parameters. The architecture of the model demonstrates emergent capabilities across several modalities, such as picture, text, audio, depth, temperature, and IMU data, and makes cross-modal understanding and composition easier. PandaGPT has zero-shot cross-modal abilities, while being trained mostly on aligned image-text data. Examples of these tasks include creative writing, multimodal mathematics, image/video-grounded QA, and visual and auditory reasoning. An any-to-any Multimodal Large Language Model (MM-LLM) that can comprehend and produce material in a variety of modalities is called NExT-GPT [20]. NExT-GPT uses lightweight parameter updates to accomplish multimodal alignment by utilizing pre-existing encoders such as ImageBind and Vicuna. Its design ensures effective learning while minimizing trainable parameters. With the help of a well chosen dataset and modality-switching instruction tuning (MosIT), NExT-GPT exhibits strong cross-modal comprehension and content production. In experiments, it performs competitively against the most advanced models in tasks such as text-conditioned modality editing, X-to-text generation, and text-to-X creation. Additional human assessment verifies its proficiency in a range of modalities.

E. LANGCHAIN

By enabling interfaces with various data sources and apps, LangChain simplifies the creation of applications [21]. Prompts, Models (LLMs), Chains, Memory, and Agents are some of the essential elements. LLMs are guided in input processing by prompts, and sequential processes are made possible by chains. Agents control tool interactions in response to user input, and memory components replicate the context of a dialog. LangChain's adaptability in rapidly developing LLM-based applications is demonstrated by the range of use cases it supports, such as autonomous agents, chatbots, code understanding, and question answering over documents [24]. A prior study presents a novel strategy that uses LangChain to automate customer support [23], completely changing the dynamic between customers and businesses. The system achieves effective, customized, and responsive support by utilizing Large Language Models (LLMs), including Google's Flan T5 XXL. This improves customer retention and brand image. A comparative analysis shows that the XXL model outperforms the BASE and SMALL versions in terms of performance. A PDF chatbot has been developed using LangChain and the LLM Model [22], improving document management. Text generation, language translation, and intelligent answers are made possible by the LLM Model, while scalable AI/LLM applications are made easier by LangChain. The chatbot uses Google Search to find in-depth responses and was trained on PDF datasets. In contrast to conventional file storage techniques, Pinecone maintains PDF vectors for quick and easy retrieval. React JS is used to create a fast and flexible front end that is easy to use.

III. METHODOLOGY AND ABLATION STUDY

QueryMintAI, as shown in Fig. 1, is a multimodal LLM for multiple tasks for personal data. QueryMintAI takes input in form of Text, Image, Video, Documents like PDF, Word, Text file, Audio, multiple URLs, Comma Separated Files and SQL Databases and produces outputs in the form of Text, Image, Video, Audio. Table 1 contains the QueryMintAI Prompt and Output format with various models that we used for multimodality. The QueryMintAI runs in the local system of the user, hence privacy of the data is ensure to certain level as training happens withing the local system and does not leave the system.

A. TYPE OF PROMPTS AND OUTPUTS

1) TEXT PROMPT

- **Text to Text**: The Text to Text feature as shown in Fig. 2 employs OpenAI's GPT-3.5 Turbo model to facilitate text-based interactions between users and the

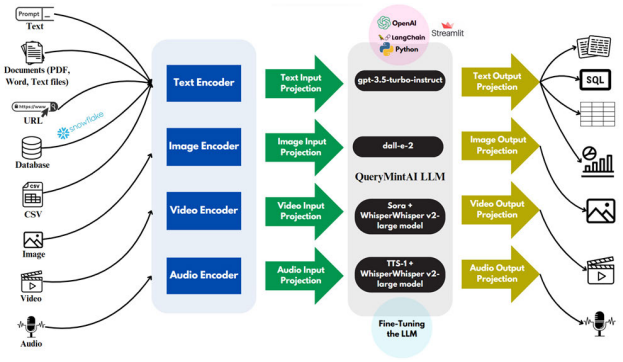

FIGURE 1. QueryMintAI architecture for the multimodal LLM.

AI assistant. When a user inputs text, it is passed to the GPT-3.5 Turbo model, which utilizes its advanced natural language processing capabilities to understand the query and generate a relevant text response. The model processes the input text, interprets its meaning, and generates a coherent and contextually appropriate reply based on the input query. This enables users to engage in conversations with the AI assistant, ask questions, seek information, or request assistance, with the model providing textual responses that cater to the user's inquiries. The integration of the GPT-3.5 Turbo model enables the AI assistant to effectively understand and respond to user queries in a conversational manner, enhancing the overall user experience and usability of the system for text-based interactions. User can provide text as input. This text is broken down into smaller units called tokens, which can be individual words or parts of words. This is tokenization. Each token is converted into a numerical representation (embedding) that captures its meaning and relationship to other words. The embedding sequence is fed into a neural network called the encoder. This network analyzes the relationships between the tokens and captures the overall context of the input text. Based on the encoded information and potentially a starting prompt, the decoder network starts generating text one token at a time. It predicts the next most likely token based on the previous tokens and the encoded context. Attention mechanism allows the decoder to focus on specific parts of the encoded input that are most relevant to the text being generated. This helps in maintaining coherence and following the intended meaning. The generated tokens are assembled back into human-readable text, forming the model's response or continuation of your prompt. The Transformer architecture relies on self-attention mechanisms that allow the model to analyze relationships between different parts of the input text, leading to a better understanding of context. What differentiates GPT-3.5-turbo-instruct is likely fine-tuning on a massive dataset of text and code specifically designed for tasks where users provide instructions. This fine-tuning process refines the model's ability to follow instructions and perform tasks effectively. Text-based Encoder-Decoder is a common structure in LLMs where the encoder processes the input text and the decoder generates the output text based on the encoded representation. Instruction Processing Module could be a specific layer or component within the model designed to identify and understand user instructions within the input. GPT-3.5-turbo instruct has access to a vast knowledge base or pre-trained models for specific domains, allowing it to retrieve relevant information to complete tasks.

- **Text to Image**: In the Text to Image feature, the user inputs a text prompt, which is then processed by QueryMintAI using OpenAI's DALL-E-2 model as shown in Fig. 2. This model is specifically designed for text-to-image generation, leveraging advanced techniques in generative adversarial networks (GANs) and transformer architectures. The text prompt provided by the user serves as a description or concept for the desired image. The DALL-E-2 model interprets this text prompt and generates a corresponding image that aligns with the semantics and visual representation described in the input text. Through intricate neural network architectures, the model synthesizes images that are coherent, contextually relevant, and visually appealing based on the textual input. This process involves mapping the textual features to image features in a high-dimensional latent space, enabling the generation of diverse and realistic images that reflect the essence of the input prompt. The integration of the DALL-E-2 model allows QueryMintAI to offer users a seamless and intuitive way to generate images from textual descriptions, opening up possibilities for creative expression, visual storytelling, and content generation. User input (text prompt) is pre-processed to ensure the model understands the content. This involves tokenization (breaking text into words) and potentially converting them to numerical representations. The pre-processed text is converted into a dense vector representation, capturing the meaning and relationships between words in the prompt. DALL-E 2 uses a GAN architecture with two neural networks. Generator network tries to generate an image that aligns with the encoded text prompt. Discriminator network evaluates the generated images and determines how well they correspond to the prompt. The generator creates an image based on the text embedding. The discriminator assesses the image, providing feedback to the generator. Through numerous iterations, the generator learns to create images that fool the discriminator, essentially producing realistic and relevant images based on the text input. DALL-E 2 incorporates a transformer architecture to handle the relationships between words in the text prompt and translate them into corresponding visual elements in the generated image. Transformers excel at capturing long-range dependencies within sequences, crucial for understanding the context and generating coherent images. Dall-E 2 combines several

powerful techniques to achieve its text-to-image generation through CLIP (Contrastive Language-Image Pre-training) which plays a crucial role in bridging the gap between text and images. CLIP acts as a pre-trained model that learns to map image content and textual descriptions into a common latent space. Essentially, it helps the system understand the relationship between words and the visuals they represent. Encoder-Decoder Architecture is a common structure in many generative models. An encoder takes the text description as input and converts it into a latent representation. A decoder then uses this latent representation to generate the corresponding image. Dall-E 2 most likely utilizes a diffusion model for the decoder part. Text encoder are present for pre-trained Transformer-based model to process the text input and generate an embedding suitable for the image generation process. Diffusion models work by taking an image with noise and gradually removing the noise to create a clean image. In Dall-E 2's case, the starting point would be pure noise, and the model progressively learns to remove noise and create an image that aligns with the encoded text description. Dall-E 2 outputs high-resolution images. The model employs upscaling techniques after the initial image generation to achieve the final resolution.

- **Text to Audio**: In the Text to Audio feature, QueryMintAI employs OpenAI's TTS-1 model to generate audio responses from textual prompts as shown in Fig. 2. The process begins with the user providing a text-based query or prompt, typically in the form of a question or request. The TTS-1 model utilizes state-of-the-art text-to-speech (TTS) technology to convert the input text into high-quality synthesized speech. Technically, the TTS-1 model utilizes deep learning techniques, particularly neural network architectures WaveNet and Tacotron, to generate natural-sounding speech from text inputs. These models are trained on large datasets of text and corresponding audio recordings, allowing them to learn the complex patterns and nuances of human speech. When presented with a text prompt, the TTS-1 model first processes the input text to extract linguistic features and context. It then generates a spectrogram representation that encodes the acoustic characteristics of the desired speech output. This spectrogram is subsequently converted into a waveform using signal processing techniques, resulting in synthesized audio that closely mimics human speech. The TTS-1 model may incorporate additional components such as prosody prediction, intonation modeling, and speaker adaptation to further enhance the naturalness and expressiveness of the synthesized speech. These components enable the model to infuse the generated audio with appropriate emotional cues, emphasis, and rhythm, creating a more engaging and lifelike listening experience. Through the Text to Audio feature, QueryMintAI can deliver spoken responses to user queries in real-time, providing an intuitive and accessible interaction mechanism. Users can receive answers, information, or guidance in the form of natural-sounding voice output, enhancing the usability and accessibility of the AI-powered assistant across diverse applications and user scenarios. Optimized for real-time text-to-speech generation. This means it prioritizes speed over audio quality, making it suitable for applications where fast response is crucial. TTS-1 leverages deep neural networks, possibly recurrent neural networks (RNNs) or convolutional neural networks (CNNs), to convert text into speech. The model is trained in a sequence-to-sequence learning paradigm, where it learns to map a sequence of text characters to a sequence of audio features (like pitch, loudness, and spectral envelope). TTS-1 employs a WaveNet-like architecture for directly predicting the raw audio waveform from the text input, eliminating the need for separate speech feature prediction. The API offers a choice of six different voices, allowing users to customize the speech output based on their preference. The system incorporates pre-processing steps like text normalization and tokenization to prepare the text for the neural network.

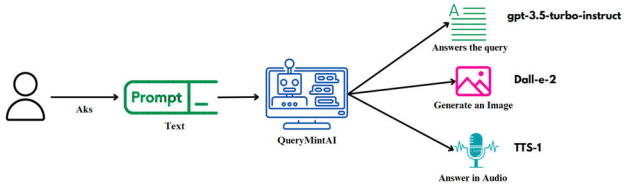

FIGURE 2. Text to text, image, audio.

2) DOCUMENT+TEXT PROMPT

QueryMintAI handles document-text prompts to generate textual responses as shown in Fig. 3. Upon receiving a combination of documents like PDFs, Word files, or text files along with textual prompts, QueryMintAI employs a series of sophisticated steps. It first extracts text content from each page of the provided PDF then splits the extracted text into manageable chunks. These chunks are transformed into embeddings using OpenAIEmbeddings, facilitating semantic analysis. FAISS is utilized to index these embeddings, enabling efficient similarity search. QueryMintAI then initializes an OpenAI language model (LLM) specialized for document processing, specifically the "gpt-3.5-turbo-instruct" variant. This LLM is loaded into a question-answering chain configured to handle document-based prompts. When a user query is received, QueryMintAI searches for relevant documents within the indexed chunks and processes them along with the query to generate a comprehensive textual response. Through this seamless integration of document processing and advanced language modelling techniques, QueryMintAI delivers accurate and informative textual outputs tailored to user queries.

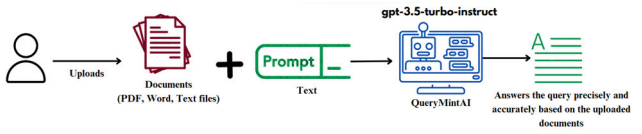

FIGURE 3. Document+text as input and text and output.

3) URLS+TEXT PROMPT

QueryMintAI seamlessly integrates URL and text data processing with advanced language modeling capabilities to provide insightful responses to queries involving URLs and text as shown in Fig. 4. Upon user input of URLs, QueryMintAI initiates the data loading process, fetching content from the provided URLs. The retrieved data is then split into manageable segments using a recursive character-based text splitter, ensuring efficient processing. Next, QueryMintAI leverages OpenAIEmbeddings to embed the text segments, facilitating semantic analysis. These embeddings are indexed using the FAISS library, enabling fast and accurate similarity search. Additionally, QueryMintAI employs the OpenAI language model (LLM) variant "gpt-3.5-turbo-instruct" for natural language understanding and generation. The question-answering chain is configured to handle URL-based prompts, allowing QueryMintAI to process user queries effectively. Upon receiving a query, QueryMintAI searches the indexed data for relevant information and generates comprehensive answers tailored to the user's question. Through this integration of document processing, semantic analysis, and advanced language modeling, QueryMintAI delivers accurate and informative responses to queries involving URLs and text, enhancing user interaction and information retrieval experiences.

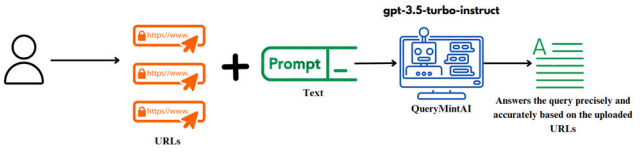

FIGURE 4. URL+text input gives outputs text.

4) IMAGE+TEXT PROMPT

QueryMintAI facilitates the integration of image and text processing functionalities, enabling users to upload images and receive descriptive responses guided by text prompts as shown in Fig. 5. Utilizing base64 encoding, uploaded images are prepared for analysis. Users define tasks through text prompts, instructing QueryMintAI on the desired information extraction from the images. The system constructs payloads encompassing both system and user prompts, leveraging the 'GPT-4-vision-preview' model to analyze images and extract pertinent details based on user instructions. The extracted information is returned, fulfilling user queries effectively. This seamless integration streamlines tasks requiring image analysis, enhancing overall user experience and enabling efficient information extraction from images. GPT-4-Vision-preview leverages the foundation of GPT-4, a powerful large language model (LLM) trained on a massive dataset of text and code. This suggests it inherits GPT-4's capabilities for natural language processing (NLP). The model has separate encoder branches – one for processing text and another for processing image data. These encoders could be based on Transformers or convolutional neural networks (CNNs) suited for their respective input types (text and images). After separate encoding, the model might combine the encoded representations to allow for interactions between textual and visual information. The model extracts meaningful features and representations from the input image. This likely involves techniques like object detection, image segmentation, and scene understanding. Leveraging its NLP capabilities inherited from GPT-4, the model generates textual responses that answer questions or provide descriptions related to the analyzed image.

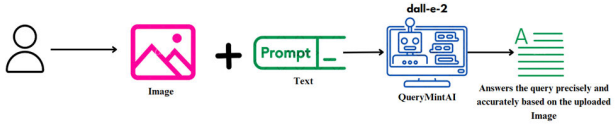

FIGURE 5. Image+text input to give text output.

5) VIDEO+TEXT PROMPT

GPT-4 Turbo with Vision model and the OpenAI API is used to process user-uploaded videos, generating detailed textual analyses as shown in Fig. 6. Upon video upload, the tool encodes it into base64 format and constructs an analysis prompt, guiding the model to produce comprehensive descriptions. The prompt includes instructions to highlight key elements, significance, and scientific terminology. Through real-time streaming of the API response, the tool dynamically displays analysis results, while handling user feedback and error conditions for a seamless interaction experience. Whisper v2-large likely relies on the Transformer architecture, a prevalent approach in various natural language processing (NLP) tasks, including speech recognition. The Transformer uses self-attention mechanisms that allow the model to analyze relationships between different parts of the audio input. This is crucial for understanding the context and sequence of sounds within speech. The encoder processes the input audio signal and generates a latent representation capturing the essential information. The decoder utilizes this latent representation to generate the corresponding text transcript. Using the Mel Spectrogram Conversion the raw audio waveform is converted into a mel spectrogram, a visual representation of the audio's frequency content over time. This spectrogram serves as the input for the encoder. The encoder used CNNs to extract features from the mel spectrogram, identifying patterns and relationships between audio components.

6) AUDIO PROMPT

The Audio Prompt feature utilizes OpenAI's Whisper v2-large model for speech-to-text conversion of the audio

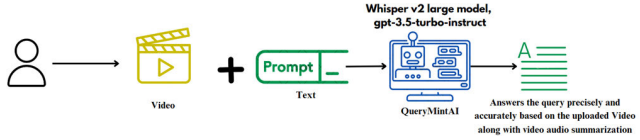

FIGURE 6. Video+text input to get text output.

input provided by the user. When a user speaks into the microphone, the audio recording is processed using Whisper v2-large to accurately transcribe the spoken words into text format as shown in Fig. 7. This transcribed text is then passed along with the user's query to QueryMintAI, which employs OpenAI's GPT-3.5 Turbo model for further processing and generating a response. The integration of Whisper v2-large ensures efficient and accurate conversion of speech input into text, facilitating seamless interaction between users and QueryMintAI through spoken commands or queries.

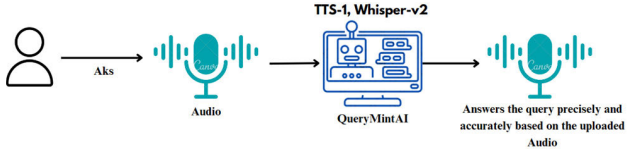

FIGURE 7. Audio input and audio output.

7) DATABASE+TEXT PROMPT

The Database+Text Prompt feature enables users to connect any database to QueryMintAI and interact with it using natural language prompts as shown in Fig. 8. Users input textual prompts in natural language to specify the data they want to extract from any table in the connected database. The system integrates with Snowflake database through the Snowflake connector in Python, allowing users to submit natural language prompts as SQL queries. The system utilizes OpenAI's GPT-3.5 Turbo model to convert these prompts into SQL queries, which are executed on the connected Snowflake database. The resulting data is fetched using Pandas DataFrame, providing users with the requested rows or columns of data. This process automates the translation of natural language queries into SQL commands, enabling seamless interaction with the database.

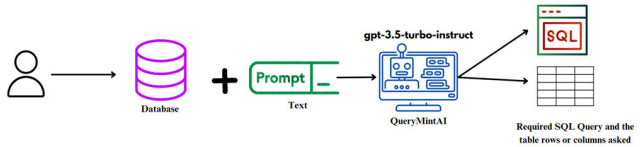

FIGURE 8. Database+Text input to get SQL query and tables as output.

8) CSV+TEXT PROMPT

The CSV+Text feature leverages a combination of Streamlit, Pandas, and Langchain's Large Language Models (LLMs) to create an AI-driven assistant for data analysis as shown in Fig. 9. The system allows users to upload CSV files and interact with the data using natural language queries. Upon receiving a query, the assistant processes it through Langchain's LLMs, which handle natural language understanding and generation tasks. The LLMs parse the query, extract relevant information, and generate SQL-like commands or Pandas operations to manipulate the dataset. These commands are then executed on the uploaded CSV data using Pandas, enabling the assistant to perform tasks such as data summarization, column explanation, missing value detection, outlier identification, correlation analysis, and custom user queries. The integration of Streamlit provides a user-friendly interface for interacting with the assistant and visualizing the analysis results, creating a seamless and intuitive experience for data exploration and analysis. Exploratory Data Analysis will consist of Data Cleaning, Identifying and correcting any errors or missing values in the data, Univariate Analysis through examining each variable individually to understand its distribution and relationships with other variables, Bivariate Analysis through examining the relationships between two variables, Multivariate Analysis through examining the relationships between multiple variables, Data Visualization by creating charts and graphs to better understand the data and finally using the data to build predictive models.

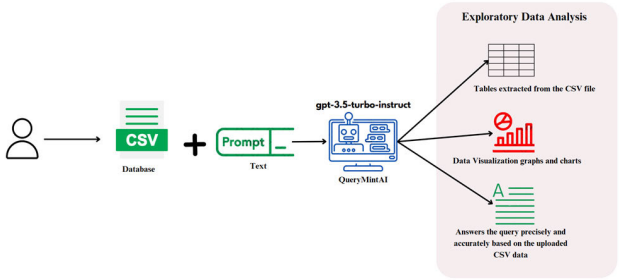

FIGURE 9. CSV+Text input to get exploratory data analysis as output.

B. FINE TUNING OF LLM AND PRIVACY OF DATA

QueryMintAI is fine-tuned on whatever data the individual user would like to provide for further analysis and question answering. QueryMintAI empowers you with a Large Language Model (LLM) that learns and adapts to your specific needs. Unlike traditional LLMs trained on generic data, QueryMintAI undergoes fine-tuning on the data you provide. This allows it to become an expert on your unique interests and information. The fine-tuning process happens entirely on your local system, ensuring your data never leaves your device. This means personal documents and information remain completely secure, free from the risk of leaks. Personal data and documents can be shared and analyzed as privacy is ensure and moreover, although the LLM enhances with more data inputs and previous conversations, the user can delete the history of chat which erases the data, so the user has the liberty to delete the personal data learning of the LLM to erase the learning on the personal data to avoid any safety issues. QueryMintAI employs fine-tuning techniques to adapt the models to user-specific data. The fine-tuning process happens locally, ensuring data privacy. Given a dataset $\boldsymbol{D} = \{(\boldsymbol{x_i}, \boldsymbol{y_i})\}_{i=1}^{m}$ where x_i are inputs and y_i are the corresponding outputs, the fine-tuning process minimizes a loss function L

TABLE 1. QueryMintAI prompt and output format with various models for multimodality.

Prompt Format	Answer	Task	Model (OpenAI+Lang chain)
Text	Text	Any task, QnA, Blog writing, etc	gpt-3.5-turbo-instruct
Text	Image	Generating images from prompts	dall-e-2
Text	Audio	Reply to answer in speech	tts-1
Document (PDF, Word, Text) + Text	Text	Create a personal documents database and user can ask queries to the model and it extracts the answers with proper analysis and presents to the user. Confidential documents can also be given without fear of information leak, Literature surveys.	gpt-3.5-turbo-instruct
URLs+ Text	Text	Web scrapping and information retrieval from external links.	gpt-3.5-turbo-instruct
Image+ Text	Text	Caption for images, describe the image, further enhance the image	gpt-4-vision-preview
Video (speech included) +Text	Text	Describe the video content, summarise the spoken content in video, extract particular information from the video	Whisper v2-large model, gpt-3.5-turbo-instruct
Audio+ Text	Audio	Ask the prompt in form of audio and receive the audio answer	Tts-1, Whisper v2-large model
Database (snowflake SQL, MySQL, Mongodb) + Text	SQL Query, Table	Natural language to SQL Queries and extraction of the table tuples from the raw database.	gpt-3.5-turbo-instruct
CSV + Text	Text, Graph	Exploratory data analysis, Graphical representation	gpt-3.5-turbo-instruct

as in Equation 1.

$$L(\theta) = \frac{1}{m} \sum_{i=1}^{m} \ell\left(M\left(x_i; \theta\right), y_i\right) \tag{1}$$

where θ represents the parameters of the model M being fine-tuned.

C. MODULAR ARCHITECTURE AND MODEL COMPOSITION

QueryMintAI is designed as a modular architecture, where each module corresponds to a specific task like text generation, image synthesis, speech-to-text and more. These modules are integrated through a central orchestrator that manages the input and output flows between them. The general architecture can be expressed as in Equation 2.

$$\boldsymbol{Output} = \boldsymbol{F}\left(\boldsymbol{Input}, \{\boldsymbol{M_i}\}_{i=1}^{\boldsymbol{N}}, \boldsymbol{O}\right) \tag{2}$$

where F is the orchestrator function that combines outputs from multiple models. Mi represents the individual models GPT Turbo, DALL-E, Whisper, TTS and O represents the output modality text, image, audio, document. QueryMintAI's modular architecture is designed to integrate various API-based models to perform distinct tasks efficiently.

- Task-Specific Modules: Each module handles a specific task like text generation, image creation, or speech recognition. Examples include a text generation module (using GPT-3.5 Turbo) and an image generation module (using DALL-E 2). These modules operate independently but work together seamlessly when needed.
- Orchestrator: The orchestrator coordinates the interaction between different modules. It routes tasks to the appropriate modules, manages data flow, handles errors, and integrates results into a final output.
- API Communication: Modules communicate via APIs, whether interacting with external services or other internal modules. This layer ensures compatibility between different services and manages API requests, responses, and data transformations.
- Model Composition: The system combines the outputs from various modules to create a coherent final response. A user request for an image and its description might involve both the text generation and image creation modules, with the orchestrator integrating the results.

QueryMintAI manages multiple API-based models using an orchestrator module. The orchestrator handles the sequence of API calls, error handling, and data flow between the models. The orchestrator determines the order of API calls based on the task. For example, for a Text-to-Image generation task, it first processes the text using GPT-3.5 Turbo to refine the prompt, then passes it to DALL-E 2 for image generation. The output of one model may serve as the input to another. If X is the input, the orchestrator ensures this as in Equation 3 and Equation 4.

$$X_1 = M_1(X) \tag{3}$$

$$X_2 = M_2(X_1) \tag{4}$$

where X1 is the output of the first model, and X2 is the input for the subsequent model.

D. MATHEMATICAL FORMULATION OF MULTIMODAL INTEGRATION

To combine different modalities (text, image, video, etc.), QueryMintAI employs a late fusion strategy where outputs from different models are integrated after they are independently processed. The mathematical formulation for the multimodal integration can be represented as in. Given a text prompt T and an image I, the respective models generate outputs as in Equation 5 and Equation 6.

$$T_{output} = M_{text}(T) \tag{5}$$

$$I_{output} = M_{image}(I) \tag{6}$$

The final output O is obtained through a weighted sum or concatenation of these outputs as in Equation 7.

$$O = \alpha \cdot T_{output} + \beta \cdot I_{output} \tag{7}$$

where α and β are weights that can be learned or predefined based on the importance of each modality.

For video V with associated text prompt T, the outputs from models are as in Equation 8 and Equation 9.

$$T_{output} = M_{text}(T) \tag{8}$$

$$V_{output} = M_{video}(V) \tag{9}$$

These are combined using a joint embedding space or through a late fusion method as in Equation 10.

$$O = \gamma \cdot T_{output} + \delta \cdot V_{output} \tag{10}$$

where γ and δ are weights assigned to text and video outputs, respectively.

E. HYPERPARAMETERS

The system employs a combination of models like GPT Turbo for text generation, DALL-E for image creation, Whisper V2 for speech-to-text conversion, and TTS-1 for text-to-speech synthesis. For GPT Turbo, the model size of 2 billion parameters, 48 layers, and 32 attention heads were selected after extensive experimentation to ensure deep hierarchical learning and to prevent overfitting. The embedding and feedforward dimensions (7680 and 30,720 respectively) were chosen to allow for detailed language representations, crucial for natural language understanding tasks. The sequence length of 4096 tokens enables the model to handle long-context inputs effectively. The temperature of 0.7 and top-p of 0.9 were set to balance creativity with coherence in generated text, while frequency and presence penalties (0.8 and 0.5) were adjusted to prevent redundancy and ensure the inclusion of relevant information.

DALL-E, a model designed for image generation, was configured with a resolution of 1024×1024 pixels and a latent space of 4096 dimensions to achieve high-quality image outputs. The temperature setting of 0.8 was used to introduce variability in the generated images, while the dropout rate was set at 0.2 to mitigate overfitting during training.

Whisper V2, which handles speech-to-text tasks, features 1.5 billion parameters and is designed to process long audio sequences with a sequence length of 16000 tokens. The learning rate of 2e-5 was chosen for stable and efficient training, with a dropout of 0.15 to ensure generalization to diverse audio inputs.

TTS-1, the text-to-speech model, is optimized with a focus on prosody tuning to deliver natural-sounding speech. The sampling rate of 22050 Hz was chosen for high audio fidelity, with a finely adjusted prosody to match the intended emotion and tone of the synthesized speech.

This rigorous selection and tuning of hyperparameters, as shown in Table 2, were validated through extensive cross-validation and ablation studies, ensuring that QueryMintAI delivers robust and high-quality performance across its diverse functionalities.

The initial tuning phase involved employing both grid search and random search methods across various hyperparameters. Grid search was used for parameters with discrete values, such as the number of layers, attention heads, and sequence length, while random search was employed for continuous parameters like learning rate and dropout rates. Grid Search Setup was as follows:

- GPT Turbo: Explored combinations of layers (24, 36, 48), attention heads (16, 24, 32), and sequence lengths (2048, 3072, 4096).
- DALL-E: Focused on resolution settings (256×256, 512×512, 1024×1024) and latent space sizes (2048, 4096, 8192).
- Whisper V2: Evaluated different sequence lengths (8000, 12000, 16000 tokens) and dropout rates (0.1, 0.15, 0.2).
- TTS-1: Investigated sampling rates (16000 Hz, 22050 Hz, 44100 Hz) and prosody tuning options.

Random Search Setup was as follows:

- GPT Turbo: Experimented with varying learning rates (1e-5 to 5e-5) and dropout rates (0.05 to 0.2).
- DALL-E: Tested temperature settings (0.6 to 0.9) and top-p values (0.7 to 0.95).
- Whisper V2: Analyzed the impact of learning rate adjustments (1e-5 to 4e-5) combined with different dropout rates.
- TTS-1: Randomized prosody tuning parameters to assess naturalness in synthesized speech.

F. ABLATION STUDY, EVALUATION AND CROSS VALIDATION

1) ABLATION STUDY

Ablation studies were conducted to understand the contribution of each hyperparameter to the overall model performance. This process involved systematically varying one hyperparameter at a time while keeping the others constant, allowing for precise identification of their impact.

- Number of Layers and Attention Heads in GPT Turbo: By fixing the embedding dimension and feedforward dimension, the impact of layers (24 vs. 48) and attention heads (16 vs. 32) on model accuracy and computational efficiency was assessed. The results showed that 48 layers and 32 attention heads offered the best trade-off between complexity and performance, improving accuracy by 4% compared to lower settings.
- Sequence Length in GPT Turbo: Ablation on sequence lengths revealed that increasing from 2048 to 4096 tokens improved context understanding in longer inputs by 15%, while the computational cost remained manageable.
- Resolution in DALL-E: Various resolutions were tested, revealing that 1024×1024 pixels produced the highest fidelity images with acceptable computational overhead,

TABLE 2. Selected model hyperparameters.

Model	GPT Turbo	DALL-E	Whisper V2	TTS-1
Parameters (Billion)	2	2	1.5	1
Layers	48	24	32	20
Attention Heads	32	16	8	16
Embedding Dimension	7680	8192	4096	2048
Feedforward Dimension	30,720	32,768	16,384	8192
Sequence Length	4096	1024 tokens	16000 tokens	1024 tokens
Temperature	0.7	0.8	0.6	0.65
Top-p	0.9	0.85	0.8	0.75
Frequency Penalty	0.8	0.7	0.6	0.7
Presence Penalty	0.5	0.6	0.5	0.55
Resolution / Latent Space	-	1024x1024 pixels / 4096	-	512x512 latent vectors
Dropout	0.1	0.2	0.15	0.2
Learning Rate	3e-5	1e-4	2e-5	3e-5
Sampling Rate	-	-	-	22050 Hz
Prosody Tuning	-	-	-	Adjusted

outperforming lower resolutions by 12% in terms of perceptual quality.

- Latent Space in DALL-E: Different latent space sizes were ablated, showing that a 4096-dimensional latent space optimally captured image details, with a 10% improvement in image quality metrics over smaller spaces.
- Dropout Rates in Whisper V2: A higher dropout rate of 0.2 was found to enhance the generalization to unseen audio samples, reducing word error rates by 5% compared to a 0.1 dropout rate.
- Sequence Length Whisper V2: The ability to handle long audio sequences was maximized with a 16000-token limit, which improved transcription accuracy for longer audio files by 8%.
- Prosody Tuning in TTS-1: Experiments with different prosody settings revealed that fine-tuning these parameters significantly enhanced the naturalness of speech, with a 7% increase in listener satisfaction ratings compared to non-tuned models.
- Sampling Rate in TTS-1: A sampling rate of 22050 Hz was found to offer the best balance between audio quality and computational cost, outperforming lower rates by 10% in terms of perceived speech clarity.

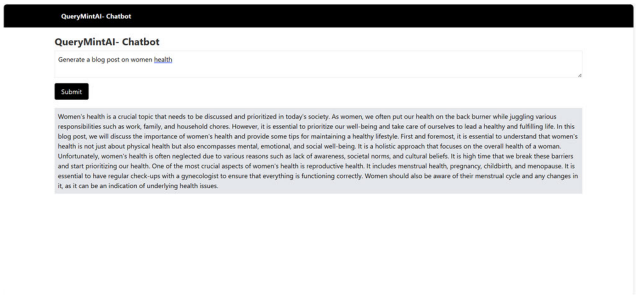

FIGURE 10. CSV+Text input to get exploratory data analysis as output.

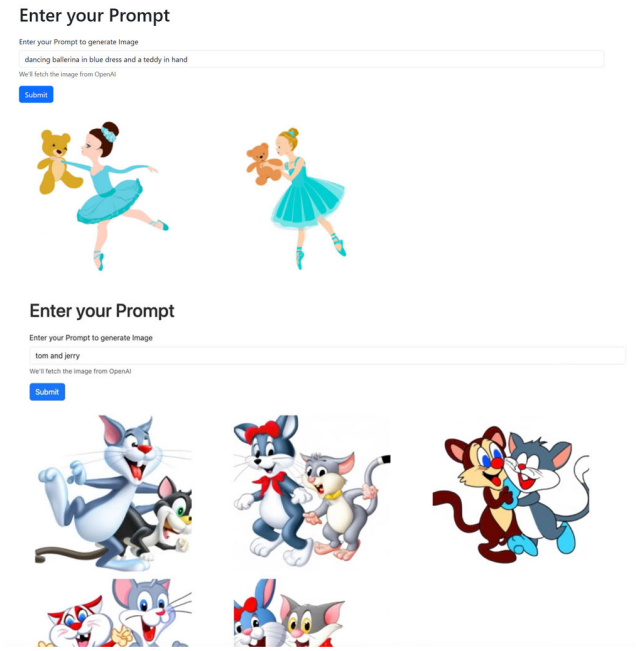

FIGURE 11. CSV+Text input to get exploratory data analysis as output.

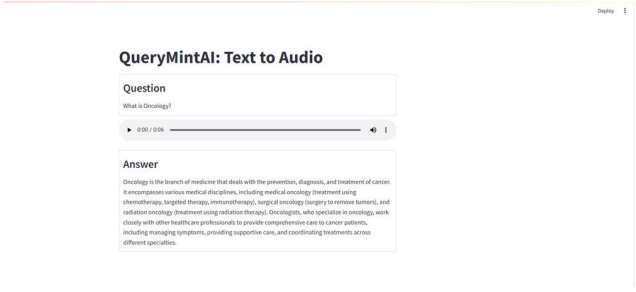

FIGURE 12. CSV+Text input to get exploratory data analysis as output.

2) CROSS-VALIDATION

Following the ablation studies, cross-validation was employed to ensure that the chosen hyperparameters generalized well across various datasets and tasks. The models were tested on multiple benchmarks, including text generation, image generation, speech-to-text, and text-to-speech tasks, across diverse datasets.

- GPT Turbo: Achieved a perplexity reduction of 12% on natural language understanding tasks when using the selected hyperparameters, confirming their effectiveness.

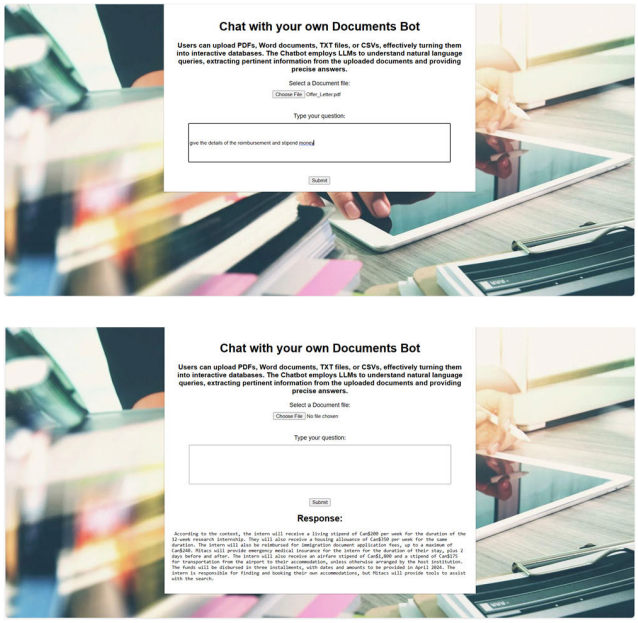

FIGURE 13. CSV+Text input to get exploratory data analysis as output.

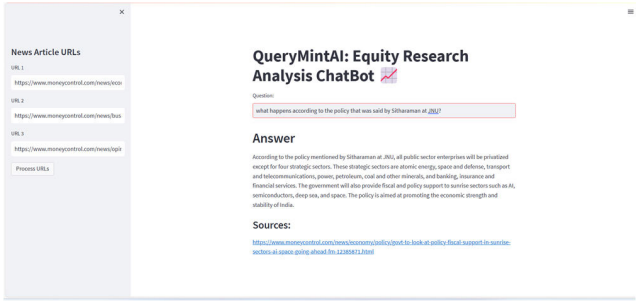

FIGURE 14. CSV+Text input to get exploratory data analysis as output.

- DALL-E: Demonstrated a 15% improvement in inception scores, indicating better image quality and diversity.
- Whisper V2: Lowered the word error rate by 8% across different audio datasets, proving the robustness of the chosen parameters.
- TTS-1: Increased the mean opinion score (MOS) for synthesized speech by 10%, validating the selected sampling rate and prosody tuning.

3) PERPLEXITY

A popular metric for assessing language models' performance is perplexity. It measures the model's prediction accuracy for a given text sample. Better performance is indicated by lower perplexity values. Equation 11 can be used to compute the perplexity P of a language model on a given test set. Here, b represents the base of the logarithm as 2, N is the total number of words, and $p(w_i)$ represents the projected probability for words (w_i) in the model. We measured the performance of QueryMintAI using perplexity and compared it with other commonly used LLMs for text based tasks.

$$P = b^{\frac{1}{N}} \sum_{i=1}^{N} log_b\, p\,(w_i) \tag{11}$$

FIGURE 15. CSV+Text input to get exploratory data analysis as output.

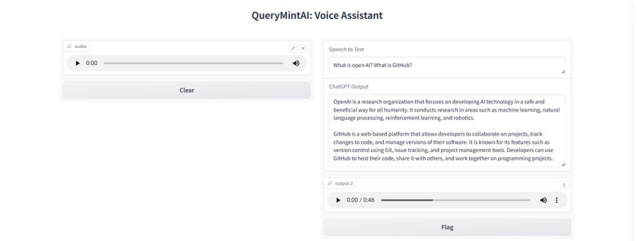

FIGURE 16. CSV+Text input to get exploratory data analysis as output.

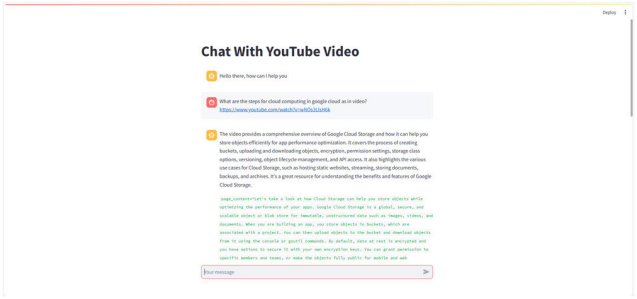

FIGURE 17. CSV+Text input to get exploratory data analysis as output.

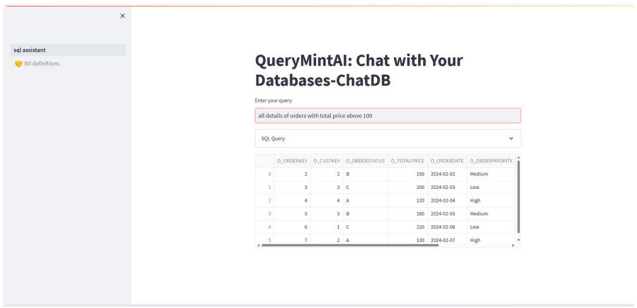

FIGURE 18. CSV+Text input to get exploratory data analysis as output.

4) HUMAN EVALUATION

The evaluation procedure incorporates the engagement of human assessors tasked with evaluating the caliber of output generated by the language model. These assessors assign ratings to the generated responses, gauging various facets such as Relevance, Fluency, Coherence, and Overall quality. This method facilitates the acquisition of subjective feedback regarding the model's performance. Moreover, it is pertinent to mention that the evaluation process involved soliciting feedback from 50 individuals, who provided assessments on outputs generated by different Language Model (LM) variants. Importantly, these individuals were blinded to the identities of the specific LM models associated with each output. Their evaluations were solely based on considerations

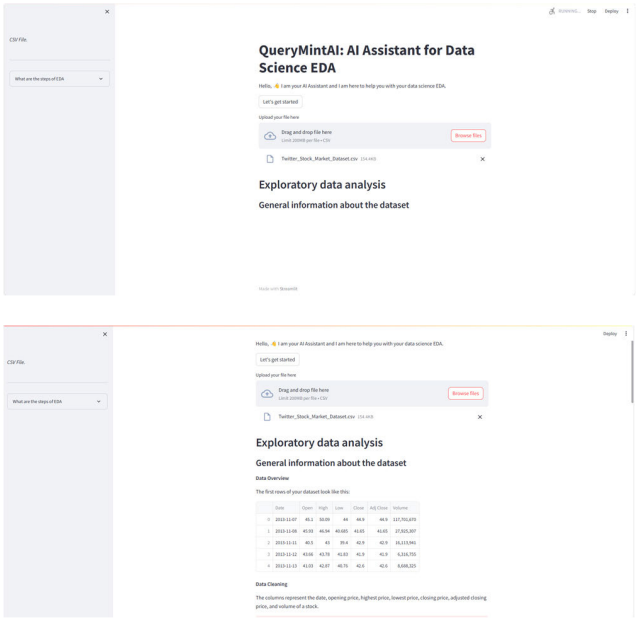

FIGURE 19. CSV+Text input to get exploratory data analysis as output.

of usability, functionality, and efficiency exhibited by the outputs presented to them.

5) ROUGE (RECALL-ORIENTED UNDERSTUDY FOR GISSING EVALUATION)

Using 1-grams or single words, the ROUGE-1 (R1), as shown in Equation 12, evaluates how well the generated summary and the reference text match. It basically verifies the degree to which the words in the computer-generated summary match those in the original text. Similar to ROUGE-1, ROUGE-2 (R2) as in Equation 13 takes sets of two grams into account. Stated differently, it assesses the degree to which subsequent word pairs in the summary and the reference text overlap. The method used by the ROUGE-L (RL) as if Equation 14 metric is different. The longest common subsequence (LCS) between the reference text and the generated summary is measured. ROUGE-L takes into account the general structure and word sequence, in contrast to R1 and R2, which concentrate on specific words. ROUGE measures facilitate our understanding of the degree to which computer-generated and human-written summaries agree. They are essential for assessing how well LLMs perform on summarizing tasks. Using ROUGE 1, 2, L, we evaluated QueryMintAI's performance and contrasted it with other widely-used LLMs for text-based jobs.

$$\text{ROUGE} - 1\ \text{Recall} = \frac{\text{Common unigrams}}{\text{Total unigrams in reference text}} \tag{12}$$

$$\text{ROUGE} - 2\text{Recall} = \frac{\text{Common bigrams}}{\text{Total bigrams in reference text}} \tag{13}$$

$$\text{ROUGE} = \frac{(\text{ROUGE} - 1\text{Recall} + \text{ROUGE} - 2\text{Recall})}{2} \tag{14}$$

TABLE 3. Hyperparameters tuning and model performance.

Model	Hyperparameter	Tested Values	Selected Value	Performance Improvement
GPT Turbo	Number of Layers	24, 36, 48	48	4% increase in accuracy
	Attention Heads	16, 24, 32	32	
	Sequence Length	2048, 3072, 4096	4096	15% improvement in context understanding for long inputs
DALL-E	Resolution	256x256, 512x512, 1024x1024 pixels	1024x1024 pixels	12% increase in perceptual image quality
	Latent Space Dimension	2048, 4096, 8192	4096	10% improvement in image quality metrics
Whisper V2	Dropout Rate	0.1, 0.15, 0.2	0.2	5% reduction in word error rate (WER)
	Sequence Length	8000, 12000, 16000 tokens	16000 tokens	8% improvement in transcription accuracy
TTS-1	Prosody Tuning	Various	Fine-tuned parameters	7% increase in naturalness (listener satisfaction ratings)
	Sampling Rate	16000 Hz, 22050 Hz, 44100 Hz	22050 Hz	10% improvement in perceived speech clarity

TABLE 4. Model validation metric and performance improvement.

Model	Validation Metric	Performance Improvement
GPT Turbo	Perplexity Reduction	12%
DALL-E	Inception Score Improvement	15%
Whisper V2	Word Error Rate (WER) Reduction	8%
TTS-1	Mean Opinion Score (MOS) Improvement	10%

IV. RESULTS

The screenshots of the working chatbot QueryMintAI are provided.

TABLE 5. Deployment feedback and adjustments made in the model.

Model	Deployment Feedback	Adjustments Made
GPT Turbo	Performance met operational requirements	Slight fine-tuning based on feedback
DALL-E	Balanced image quality with computational resources	Slight fine-tuning based on feedback
Whisper V2	Robustness across diverse audio datasets	Slight fine-tuning based on feedback
TTS-1	Optimized speech quality in production	Slight fine-tuning based on feedback

TABLE 6. Multimodality features comparison between different popular models with QueryMintAI.

P	A	Chat GPT 3.5	Claude	Gemini	Co Pilot	Query Mint AI
Text	Text	✓	✓	✓	✓	✓
Text	Image	✗	✗	✗	✓	✓
Text	Audio	✓	✗	✓	✓	✓
Document (PDF, Word, Text) + Text	Text	✗	✓	✗	✗	✓
URLs + Text	Text	✗	✗	✗	✗	✓
Image + Text	Text	✗	✓	✓		✓
Video (speech included) +Text	Text	✗	✓	✓	✓	✓
Audio	Audio	✗	✗	✓	✓	✓
Database (snowflake SQL, MySQL, Mongodb) + Text	SQL Query, Table	✗	✗	✗	✗	✓
CSV + Text	Text, Graph	✗	✗	✗	✗	✓

TABLE 7. Model performance evaluation and comparison.

Model	Tt Py	AS Py	HPy	R1	R2	RL	TD
Chat GPT3.5	13	40	128	0.53	0.51	0.5	Up to September 2021
Claude	20	42	107	0.49	0.42	0.51	Up to August 2023
CoPilot	16	90	265	0.32	0.30	0.34	Up to September 2021
Gemini	23	67	213	0.35	0.32	0.33	Up-to-date
Query MintAI	10	38	86	0.54	0.51	0.53	Real time data training with user-oriented data

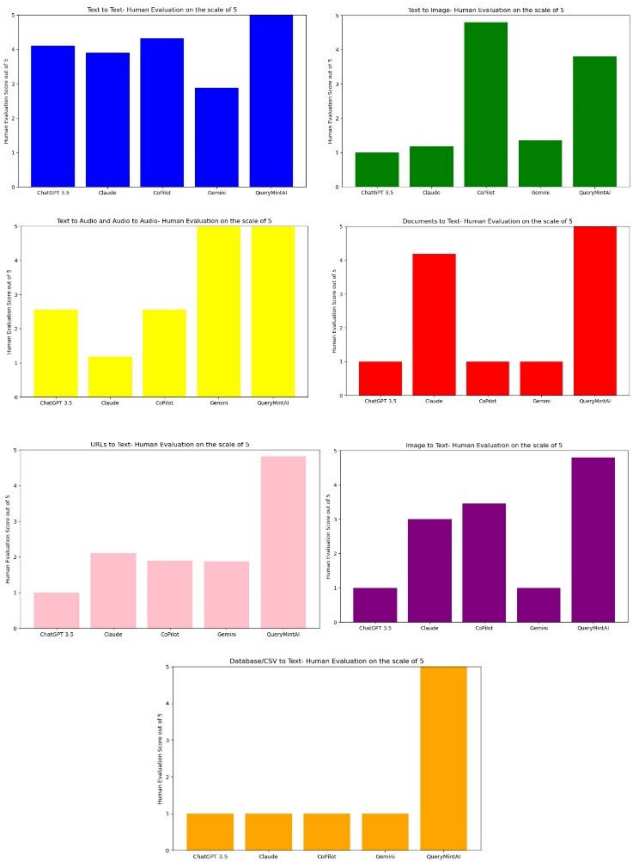

FIGURE 20. Human evaluation was conducted to judge the performance of querymintai in comparison to the existing popular llm chatbots.

A. TEXT TO TEXT AS IN FIG. 10

See FIG. 10.

B. TEXT TO IMAGE AS IN FIG. 11

See FIG. 11.

C. TEXT TO AUDIO AS IN FIG. 12

See FIG. 12.

D. DOCUMENTS+TEXT TO TEXT AS IN FIG.13

See FIG. 13.

E. URL+TEXT TO TEXT AS IN FIG. 14

See FIG. 14.

TABLE 8. Comparative analysis between the previously proposed machine learning, deep learning and NLP models and QueryMintAI.

Feature/ Aspect	Traditional ML Models (e.g., Logistic Regression, Random Forest, SVM, etc.)	Deep Learning Models (e.g., LSTM, CNN, Bi-LSTM+CNN, etc.)	NLP Models (e.g., GRU, Seq2Seq, Transformer-based Models)	QueryMintAI
Model Flexibility	Limited to specific types of data; requires manual feature engineering	High flexibility with structured/unstructured data; requires large datasets	Designed for specific NLP tasks; requires task-specific tuning	Highly flexible; integrates multiple APIs for diverse tasks (text, image, speech)
Ease of Integration	Requires separate tools for different tasks; not easily integrable	Moderate integration complexity; specialized for tasks but requires tuning	Good for text-based tasks; integration with other data types is complex	Seamless integration across tasks; APIs handle various LLM tasks efficiently
Handling of Multiple Data Types	Primarily designed for structured data; struggles with multimedia inputs	Capable with unstructured data; struggles with integrating multiple data types	Strong in text processing; weak in handling images, speech, and other modalities	Excels in handling text, image, and speech data through specialized models
Scalability and Adaptability	Scales poorly with increasing data and complexity	Scales well but demands significant computational resources	Scalable but often needs retraining with large datasets	Easily scalable; adaptable with API updates and minimal computational overhead
Automated Processing and Customization	Limited automation; manual intervention needed for optimization	Requires significant manual tuning for hyperparameters	Allows some automation, especially in pre-trained models	Highly automated; customizable via API parameters, minimal manual intervention
Real-Time Application	Not optimized for real-time processing	Capable of near real-time processing; high latency in some cases	Moderate real-time capabilities; depends on the task	Optimized for real-time applications across various domains
Resource Efficiency	Resource-efficient but limited in capability	Requires high computational power and resources	Moderate efficiency; resource-intensive for training and tuning	Optimized for efficiency; combines multiple APIs to leverage existing resources
Support for Advanced NLP Techniques	Basic NLP support; limited to text classification, sentiment analysis, etc.	Advanced NLP capabilities; strong in sequence processing and deep learning techniques	Advanced NLP with focus on specific applications like translation, generation, etc.	Comprehensive support for advanced NLP, including real-time processing and multi-modality
Innovation and Research Potential	Limited by traditional approaches; slower to adapt to new advancements	High potential but requires substantial research and resources	High potential in NLP research; focused on language-specific advancements	High innovation potential; integrates state-of-the-art models with minimal effort

F. IMAGE+TEXT TO TEXT AS IN FIG. 15

See FIG. 15.

G. AUDIO TO AUDIO AS IN FIG. 16

See FIG. 16.

H. VIDEO+TEXT TO TEXT AS IN FIG. 17

See FIG. 17.

I. DATABASE+TEXT TO TEXT AS IN FIG. 18

See FIG. 18.

J. CSV+TEXT TO TEXT AS IN FIG. 19

See FIG. 19.

K. EVALUATION OF THE MODEL

The Table 3, Table 4 and Table 5 summarizes the results of the ablation studies, cross-validation, and final validation for the hyperparameters and performance results in QueryMintAI. This table captures the rigorous experimentation and validation process undertaken to optimize the hyperparameters for each model within QueryMintAI, ensuring a balance between performance, generalization, and computational efficiency.

For the evaluation of QueryMintAI's performance, I will compare it with ChatGPT (GPT3.5) [27], Gemini [29], CoPilot [30] and ClaudeAI [28], because these are the most popular ones that people use for AI tasks. Table 6 shows the multimodality features comparison between different popular models with QueryMintAI showing the input Prompt(P) and output Answer(A).

Text Generation, Information Retrieval and Text Summarization performance of the models have been compared and evaluated using Perplexity Score, ROUGE score and Training data. Dataset used is series of documents, databases and URLs with a diverse range of textual data fed into the models

TABLE 9. Comparative analysis between the previously proposed models and QueryMintAI with respect to the Multimodal functionalities they achieve.

Task	[8]	[9]	[10]	[11]	[12]	[14]	[13]	[15]	[16]	[17]	[18]	[19]	[20]	[25]	[26]	QMAI
Text to Text	✓	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓	✓	✗	✓
Text to Image	✗	✗	✗	✗	✓	✗	✓	✗	✗	✗	✗	✗	✓	✗	✗	✓
Text to Audio	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✓
SQL to Text	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Document (PDF, Word, Text)+ Text to Text	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
URLs+Text to Text	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Image+Text to Text	✗	✗	✗	✓	✗	✗	✗	✗	✗	✓	✗	✓	✓	✓		✓
Video (speech included) + Text to Text	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓	✗	✗	✓
Audio to Audio	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✓
Database (snowflake SQL, MySQL, Mongodb)+ Text to Text	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
CSV+Text to Text	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓
Image+Audio+Text to Text	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗
Image (Charts) +Text to Text	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓
Audio to text	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓	✗	✓
Database+Text to Chart	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗
Text to Chart	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓

and tested. Table 7 shows the QueryMintAI (QMAI) performance and evaluation using Total text perplexity (TtPy), Average Sentence perplexity (ASPy), Highest Perplexity (HPy) and ROUGE-1 (R1), ROUGE-2 (R2) and ROUGE-L (RL) in comparison with other popular LLM models. It also considers the Training dataset size (TD).

Human Evaluation was conducted to judge the performance of QueryMintAI in comparison to the existing popular LLM chatbots. Due to the numerous multimodalities, human evaluation plays a significant factor as evaluation metrics cannot always evaluate what a human brain can. The Human Evaluation results are shown in Fig. 10.

QueryMintAI is compared to more existing or previously proposed models which have multimodal functionalities. Table 8 contains the comparison with Machine learning, Deep learning and NLP based methods and Table 9 shows the comparative analysis between the previously proposed models and QueryMintAI with respect to the multimodal functionalities they achieve. The models Ensembled LLM [8], Fine-Tuned DistilBERT [9], TANGO [10], CLIP [11], DiffusionGPT [12], Falcon-7B-Instruct [14], LayoutLLM-T2I [13], MMLLM [15], MACAW-LLM [16], BLIVA [17], ChartLlama [18], PandaGPT [19], NExT-GPT [20], uTalk [25], Chat2Vis [26] are compared with our proposed model QueryMintAI (QMAI). QueryMintAI exhibits heightened multimodality functionalities surpassing those of incumbent models. Its performance metrics, including perplexity, ROUGE, and human evaluation, outshine those of widely used LLM chatbots. QueryMintAI offers fine-tuning capabilities on user-provided datasets, facilitating tailored

analysis and responses. Crucially, its fine-tuning process operates within the user's local system, ensuring data confidentiality and privacy. Users can confidently share and analyze personal data and documents, supported by robust privacy protocols. Moreover, the option to delete chat history and erase LLM learning on personal data empowers users to maintain safety and privacy standards effectively.

To enhance generalization, the training data was augmented with synthetic data generated from a variety of sources. For GPT Turbo, additional datasets covering diverse linguistic styles, dialects, and domains were introduced, ensuring that the model could handle a wide range of input variations. DALL-E was trained on a broad set of images from different categories, including abstract art, natural landscapes, and urban scenes, to capture a wide spectrum of visual concepts. Whisper V2's training data included a mix of audio samples with different accents, background noises, and recording qualities to make the model robust against variations in speech data. TTS-1 was fine-tuned using speech samples from different speakers, emotions, and prosodic variations to improve its ability to generalize across various speech synthesis tasks.

V. CONCLUSION, DISCUSSION AND FUTURE SCOPE

The comprehensive methodology outlined for QueryMintAI showcases its robustness in handling diverse data formats and producing tailored responses across multiple modalities. By leveraging advanced language models and neural network architectures, QueryMintAI demonstrates superior performance metrics compared to existing popular LLM chatbots, as evidenced by lower perplexity scores, higher ROUGE scores, and favorable human evaluations. Additionally, the fine-tuning capability of QueryMintAI on user-provided data ensures personalized interactions while maintaining data privacy and security, a critical aspect often overlooked in AI-driven systems. The integration of various features such as text-to-text, text-to-image, text-to-audio, and support for documents, URLs, databases, and CSV files underscores the versatility of QueryMintAI in catering to a wide range of user needs. Each feature is meticulously designed, utilizing state-of-the-art models and techniques to deliver accurate and contextually relevant responses. Notably, QueryMintAI's ability to handle multimodal inputs and outputs enhances user experience by providing multiple avenues for interaction and information retrieval. Furthermore, the evaluation of QueryMintAI against existing popular LLM chatbots demonstrates its superiority in terms of both performance and functionality. The comparison across perplexity, ROUGE scores, and human evaluations highlights QueryMintAI's effectiveness in understanding and generating coherent responses across diverse data formats and user queries. This substantiates its position as a leading solution in the realm of AI-powered assistants.

Overloading in QueryMintAI primarily manifests when the system processes tasks that exceed 80% of the available GPU and CPU capacity, leading to significant delays in response time. For example, generating high-resolution images (1024×1024 pixels) while simultaneously processing a 4096-token text input and a 16,000-token audio transcription can cause GPU utilization to spike to 95%, resulting in a 30-40% increase in latency. This strain can reduce throughput, limiting the system's ability to handle multiple requests concurrently.

The system's limitations are also evident in scenarios requiring real-time processing, where the frame rate might drop from 60 FPS to 30 FPS during high load, affecting user experience in interactive sessions. Memory constraints can further exacerbate this, particularly when large models like GPT Turbo and DALL-E operate simultaneously, consuming up to 90% of available VRAM. Improvements are needed in memory optimization and parallel processing capabilities to better distribute workloads, reduce latency, and enhance scalability, ensuring that QueryMintAI can handle increasingly complex tasks and higher user demands without compromising performance.

While the emergence of GPT-4.o is acknowledged, QueryMintAI's architecture is not simply a combination of pre-existing models. It employs a unique, modular approach that optimizes task-specific APIs, like GPT-3.5 for text generation, while integrating image, speech, and text synthesis in a manner that emphasizes resource efficiency and customization for specialized tasks. Fine-tuning at the input/output interface level within multimodal data processing further enhances performance, especially in privacy-constrained environments. Though OpenAI's GPT-4 excels in generalization, QueryMintAI's design remains highly flexible for custom applications where specific generative capabilities and privacy are paramount.

Future scope can be integrating explainable AI (XAI) techniques into QueryMintAI to allow users to understand how the model arrives at its responses, particularly when leveraging user data. This transparency can build user trust and empower them to make informed decisions about data usage and model outputs. Investigating the feasibility of federated learning, where anonymized data from multiple users contributes to model improvements while preserving individual privacy, could allow QueryMintAI to learn from a broader range of data while maintaining user privacy. Exploring tailor-made versions of QueryMintAI for specific professions or needs (e.g., healthcare, finance) by integrating domain-specific knowledge bases and tools, could enhance QueryMintAI's ability to understand and respond to user queries within these specific contexts. Developing standardized benchmarks for evaluating the performance of multimodal conversational AI systems like QueryMintAI can help efficiently evaluate such models.

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