

Original Article

LLM Agent Integrated with TENS Device for the Treatment of Neck Pain in Teleworking

Ricardo Yauri¹, Juan Balvin², Renzo Lobo²

¹Universidad Nacional Tecnológica de Lima Sur, Lima, Perú.

²Universidad Nacional Mayor de San Marcos, Lima, Perú.

¹Corresponding Author : ryauri@untels.edu.pe

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Abstract - This research focuses on the need to monitor and treat cervical muscle pain in the context of teleworking, combining electrotherapy with artificial intelligence, with agents that use Large Language Models (LLMs) and Retrieval Augmented Generation (RAG), to offer contextual assistance and improve the effectiveness of physiotherapy therapies. In relation to the problem, during the COVID-19 pandemic, teleworking was promoted globally, which brought benefits of flexibility, generated ergonomic risks, an increase in musculoskeletal disorders, and work-related stress, affecting occupational health, making the need for LLM-RAG agents necessary to help with home therapies. The literature review revealed technological dependence on electrostimulation devices, the development of solutions adapted to different contexts, and the use of intelligent LLM-RAG agents in healthcare to provide therapeutic recommendations. Therefore, this research describes the design and implementation of an intelligent therapeutic system that integrates a TENS device controlled by an Android mobile application and assisted by an LLM-RAG agent to relieve neck pain in teleworkers through controlled signal generation and contextualized consultation connected to a vectorized document database. The results show the integration of electronic hardware, a mobile application, and an LLM-RAG agent to generate therapeutic signals, protect the hardware through current control, structure a vectorized document database with more than 170 fragments, answer queries with semantic accuracy between 94% and 98%, and average interaction time of less than 3.2 seconds.

Keywords - Nerve stimulation, TENS, LLM, RAG, Python, Cervical Muscle Pain.

1. Introduction

Currently, monitoring cervical muscle pain during teleworking arises as a response to the health challenges generated by the coronavirus disease pandemic and the growing implementation of teleworking. Electrotherapy has become an essential component of physiotherapeutic practice, as it helps alleviate muscular discomfort and supports the regeneration of injured tissues through the use of electrical stimulation [1, 2]. This therapeutic approach aims to reduce pain and inflammation while preventing the development of persistent muscular disorders [3, 4]. In parallel with the development of devices for pain treatment, such as electrotherapy, new technologies based on artificial intelligence have emerged to improve the effectiveness of therapies. In particular, Large Language Models with Augmented Retrieval (LLM RAG) agents make it possible to provide contextual assistance to the user by using information search mechanisms in databases, with health systems in teleworking environments where direct access to professionals may be limited [5, 6]. For this reason, the use of an LLM-RAG agent can be used to combine a large-scale language model with an information retrieval mechanism

from a vectorized knowledge base that generates contextualized responses based on general knowledge of the model and information sources, such as databases, documents, and web pages, among others. In 2020, the COVID-19 pandemic caused an increase in the implementation of teleworking, being the preferred work modality in various regions such as Latin America, the Caribbean, and other parts of the world [7, 8]. Although this modality provided flexibility and time management, it brought technical challenges, occupational stress, and technological difficulties [9, 10]. Several studies have shown that the lack of adequate ergonomics in the remote work environment has generated negative impacts at the musculoskeletal level, favoring the appearance of Musculoskeletal Disorders (MSDs) [11, 12]. In this framework, the International Labor Organization (ILO) noted that work-related stress represented the main occupational health problem, being responsible for 50% of occupational diseases [13, 14]. For its part, the World Health Organization (WHO) estimates that these disorders affect between 13.5% and 47% of the global population [15, 16]. In this context, the integration of LLM agent-based technologies with RAG represents a suitable alternative, but it presents



integration challenges. While these agents allow for contextualized assistance, their implementation poses challenges related to clinical data interpretation, information privacy, and response comprehension [17, 18]. Furthermore, the dependence on connectivity and misinterpretation of suggestions without professional supervision could limit their application in certain contexts [19, 20]. Therefore, it is essential to design these systems in a user-centered way so that they can be integrated into digital health environments such as TENS electrostimulation.

There are currently studies to be conducted regarding this research gap, as no solutions have been found that utilize both hardware for therapies and the use of RAG agents in physiotherapy. The systems that have been found typically only perform signal generation, pain relief procedures [1, 4], or text recommendation techniques [5, 6]. Furthermore, most TENS systems operate without patient connection or feedback. This lack of analysis indicates the need to research architectures that integrate the use of electrical therapies and RAG agents to contribute to the accessibility of home treatments. The novelty and contribution of this research focus on showing the procedure for integrating an LLM-RAG agent with a TENS system, enabling contextual interaction. Unlike previous studies that develop separate solutions for electrostimulation [3] or AI-based virtual assistance [5], this proposal integrates both solutions through a mobile application that connects the physical device with an LLM-RAG agent. Therefore, the system represents a state-of-the-art advancement by explaining the development procedures of a user-centric platform that enables real-time assistance.

This research aims to design an intelligent therapeutic system that integrates a TENS device and an LLM RAG agent to mitigate neck pain in teleworkers, using a mobile application. The system consists of six stages: signal generation, conditioning, amplification and protection, information vectorization, development of the RAG agent, and its integration with a web service for interaction via a mobile application. This system provides an accessible technological alternative in home digital health settings. In addition, ethical aspects are being considered to facilitate information management in electrical therapy applications, considering that requesting authorizations for future improvements is necessary.

2. Literature Review

In the literature review, prototypes of TENS and EMS electrical stimulators were found [21, 22]. In addition, electrostimulation equipment using H-bridges and Buck converters was developed [11, 23, 24]. Electrostimulation devices are used by medical personnel to reduce stress [25] and in clinics to control current [26]. Other applications consider muscle electrostimulation in rural settings [27] or for overweight people [28]. Artificial intelligence models for electrical stress therapies have contributed to patient

monitoring using invasive sensors or machine learning for healthcare processes [29]. These solutions can be used in remote treatment or telehealth applications, complemented by image processing and deep neural networks (PoseNet and MediaPipe) in physiotherapy [30]. Furthermore, mobile sensor-based solutions share the goal of optimizing functional recovery [29, 30]. However, in resource-limited settings, there are barriers related to infrastructure availability and staff training, which can be addressed by integrating telemedicine and telerehabilitation [31].

In recent years, intelligent agents based on LLM-RAGs have gained relevance in healthcare, particularly in medical recommendation and assistance tasks [29]. Some articles have shown that these agents can be integrated with clinical databases to provide explanations about diagnoses and therapeutic protocols [30, 31]. Similarly, other studies highlight the potential of LLM-RAGs to reduce the cognitive load of medical staff by offering clinical recommendations based on documents with vectorization techniques [32], where information validation is necessary and results must be supervised to avoid errors that may affect the patient [33].

In parallel, the integration of RAG LLM agents in mobile or desktop applications has been explored, where some studies describe that they can communicate with cloud services to make queries about their treatments and receive answers in natural language [32, 33], providing contextualized information. The understanding of the recommendations depends on the interface design and the language used, which can represent a barrier in populations with low levels of digital or technical literacy.

3. Materials and Methods

Before the development phases, the usage protocols were reviewed to ensure compliance with ethical standards in research. Therefore, regarding participant selection and data collection, the research was conducted using simulated usage scenarios to evaluate the system's response. Its development focused on verifying the stability of signal generation and its interaction with the mobile interface and the RAG agent. The data collected corresponds to system operating parameters, such as current regulation, response time, and the agent's semantic accuracy, excluding personal or medical information. A TENS device with a graphical interface was designed for the treatment of neck pain in teleworking teachers. The system consists of the following elements: Signal generation via a microcontroller, inversion, and amplification stages. The device is controlled by a mobile app, which communicates via Bluetooth to configure device parameters such as the type of therapy and the intensity of the electric current. In parallel, the mobile application connects to a web service that links to an LLM-RAG agent, which accesses a vectorized document database to answer user questions about the treatment (Figure 1).

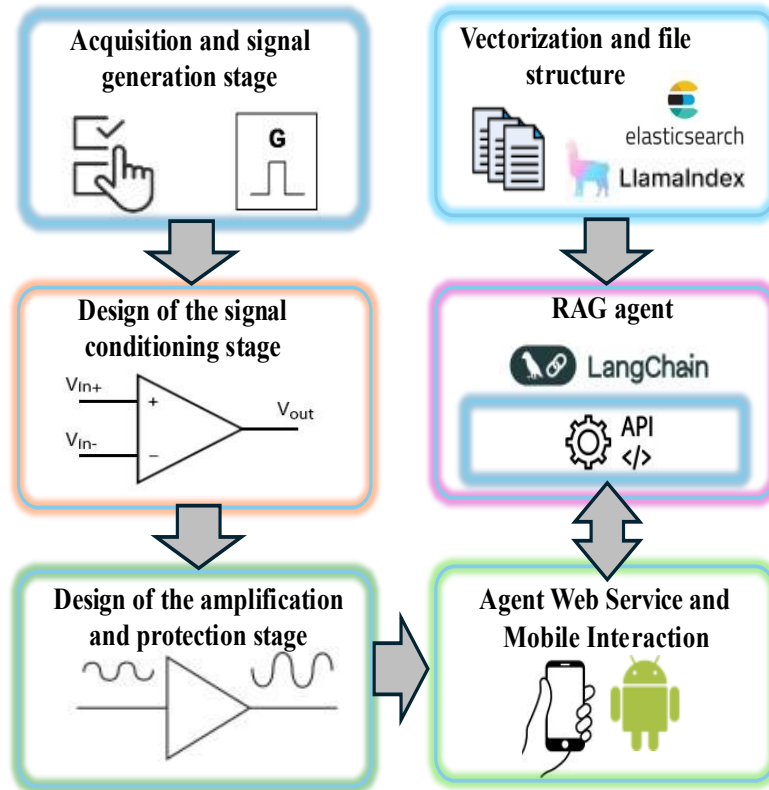


Fig. 1 General diagram of TENS device design

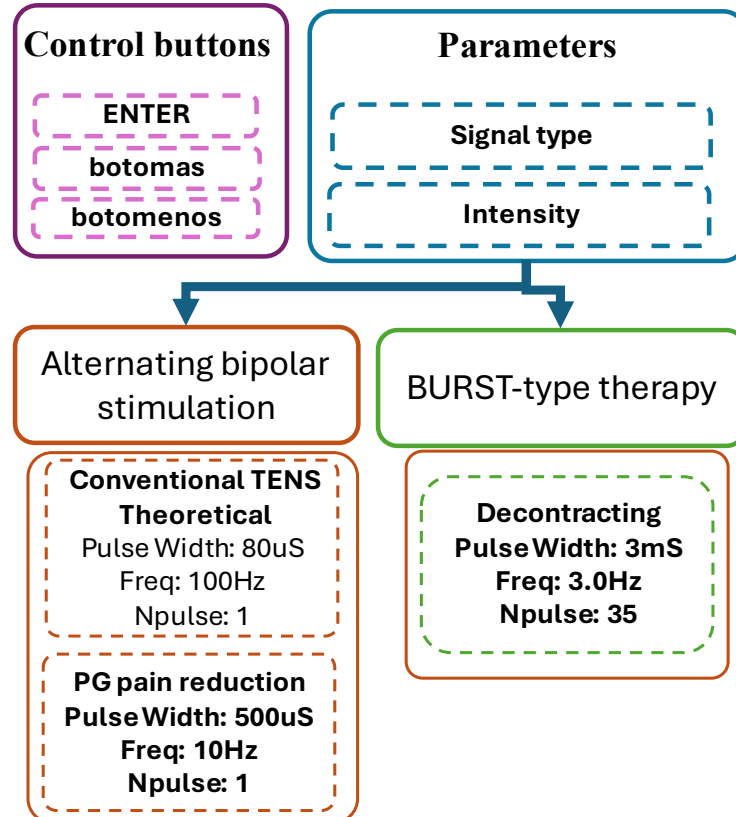


Fig. 2 Flowchart of the therapy selection interface

3.1. Signal Acquisition and Generation Phase

The functioning of the TENS unit involves capturing and producing electrical signals to guarantee both the precision and safety of the stimuli applied in the treatment of different ailments through electrical stimulation.

3.1.1. Signal selection

Alternating Current (AC) is converted to Direct Current (DC) for TENS device voltages by the 7918 voltage regulator, generating voltages between 17.3 VDC and 18.7 VDC. The system allows the selection of therapeutic stimulation patterns with three main buttons: "ENTER", "botomas", and "botomenos", adjusting parameters such as signal type and intensity (Figure 2). The produced waveforms consist of alternating bipolar stimulation and BURST-type therapy. In contrast, the BURST pattern is specifically designed for treatments aimed at muscle relaxation, operating at a frequency of 3 Hz with a pulse duration of 3 ms.

3.2. Signal Conditioning Stage Design

Before transmission and application to the processing module, the electrical signals undergo processing and conditioning. At the outset, one of the outputs produced by the

ATmega328P microcontroller is inverted using a unity-gain inverter circuit for pulses ranging from 0 Vdc to 5 Vdc.

Subsequently, in the signal coupling stage, the original signal and the inverted signal from the microcontroller are combined. For this purpose, the LM318N amplifier is used for the coupling circuit, for signal superposition and preparation (Figure 3).

3.3. Amplification and Protection Stage Design

As illustrated in Figure 4, the transmission of signals and the safety of the user are guaranteed by a circuit stage dedicated to regulating intensity and limiting current flow.

To manage the intensity, a DS1804 integrated circuit is employed to control the resistance of the circuit and adjust the waveform accordingly.

Pins 1 and 2 allow variation of the circuit resistance, while pin 3 interfaces with the Atmega328p microcontroller responsible for generating the therapeutic waveform. For signal amplification, a Class B amplifier was implemented using a 2N3055 (NPN) transistor.

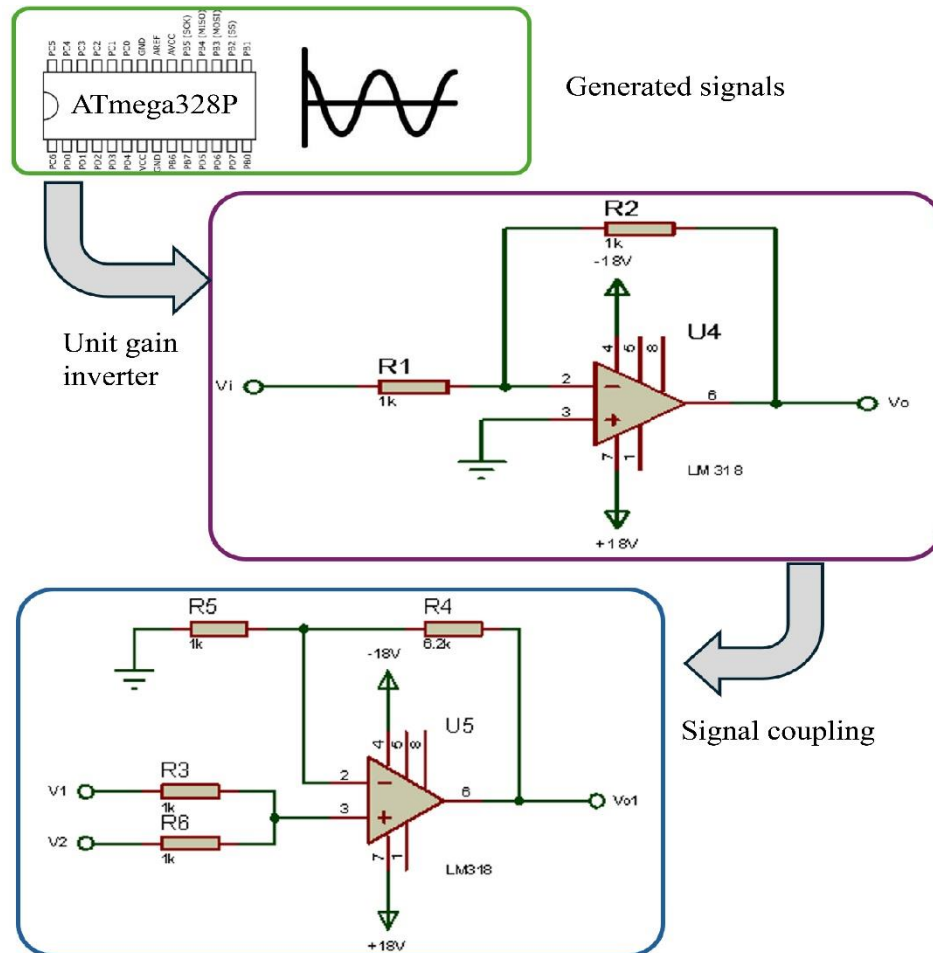


Fig. 3 Schematics of the inversion and coupling stages

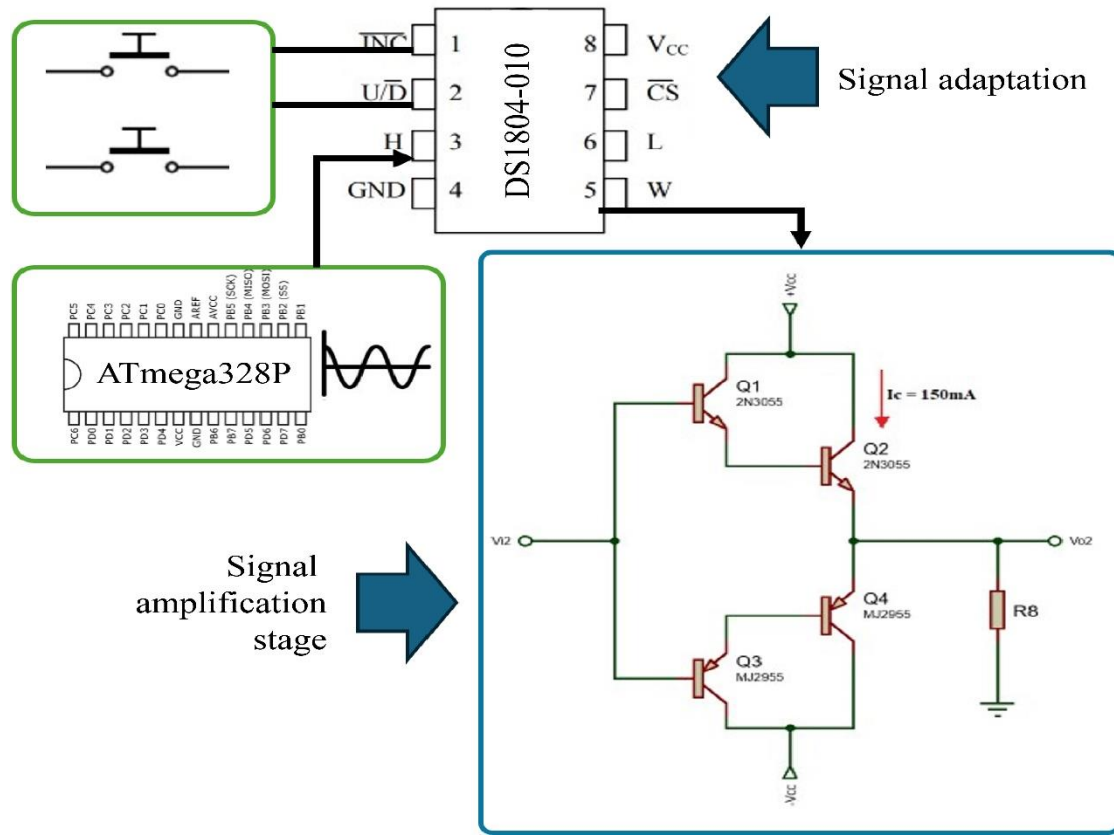


Fig. 4 Regulation and signal enhancement stage

3.4. Vectorization and File Structure

In this stage, the knowledge necessary for the operation of the LLM RAG agent is organized and structured. Technical documents, TENS device user guides, basic literature on electrical therapies, and protocols for neck pain treatment are collected. These documents are converted into text fragments (chunks) using llamaIndex, processed, and stored using semantic vectorization embedding techniques using a storage

script with the Python agent creation framework called LangChain. Each fragment is stored in a vector database in the cloud.elastic service, and its access is managed using the Python tool elasticsearch.

This vector structure represents the retrieval core of the RAG agent, as it allows the most relevant information to be identified based on the user's query (Figure 5).

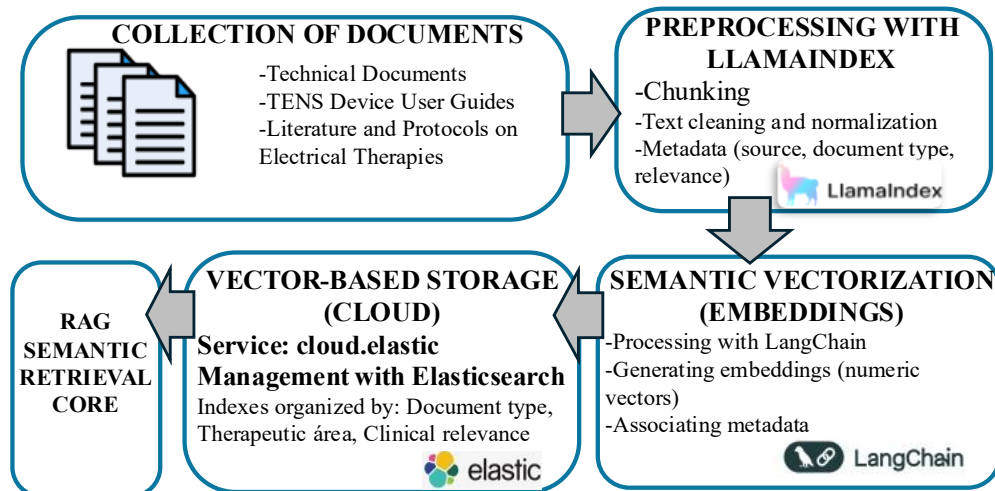


Fig. 5 Vectorization and structure process for LLM RAG Agent (TENS/THERAPY)

3.5. RAG Agent

The RAG agent is deployed as a web service that integrates components from Flask, LangChain, and OpenAI LLM models. Requests from the mobile app are received through an API developed with Flask, which channels the query to the agent core. This agent employs a REACT

approach that allows it to select the tools to respond to the query. It first uses the VectorstoreRetrieverTool tool to search the vector database (stored in cloud.elastic) for the most relevant fragments related to the detected intent (Figure 6). The LLMChain tool then synthesizes the final response using the GPT-4 model using the tools described in Table 1.

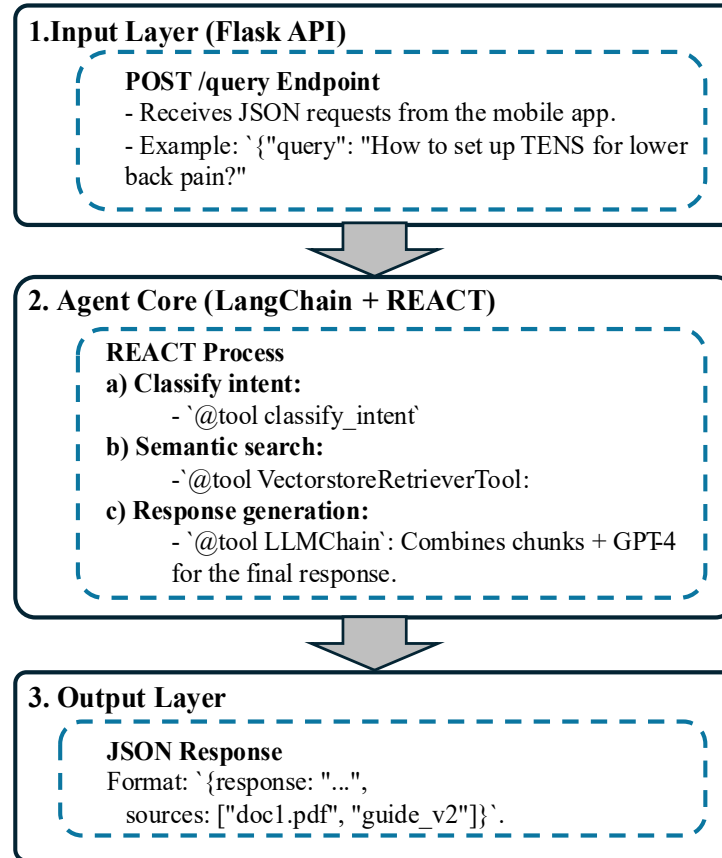


Fig. 6 Block diagram: RAG agent process

Table 1. Tools that the agent uses to respond

@Tool	Purpose	Technology
<code>get_relevant_documents</code>	Retrieve fragments from the cloud.elastic	LangChain + Elasticsearch + FAISS
<code>summarize_chunks</code>	Summarize the fragments in natural language	LangChain
<code>generate_response_llm</code>	Response based on the query and the retrieved fragments	OpenAI GPT-4
<code>validate_user_query()</code>	Analyze the user's intent and validate that it is an answerable query	Python + LangChain

3.6. Agent Web Service and Mobile Interaction

The mobile app developed in App Inventor establishes a Bluetooth connection with the TENS device's ATmega328P microcontroller, allowing commands to be sent to control the therapy. Upon selecting a therapeutic signal type, such as bipolar or burst, the app transmits coded commands (`"s1mas"` for bipolar, `"s1minus"` for burst), which the microcontroller interprets to initiate configuration. The signal intensity is also

adjusted using the "+" and "-" buttons, associated with the `"i1mas"` and `"i1minus"` commands, sending pulses that increase or decrease the circuit's output. The application sends information to the App Inventor web component in JSON format, which considers the user type (patient or technician), therapy configuration, and the user's query as data. This data is sent to the application and published in the Render service, which provides a RESTful service using the Flask framework.

This application uses Flask to integrate an agent that accesses a vector database, displaying the result on the smartphone screen (Figure 7).

4. Results and Discussion

4.1. Examination of the Signal Capture and Production Phase

The frequency values (Table 2) have a variation of less than 2% at frequencies below 60 Hz and around $\pm 1\%$ at frequencies of 49 Hz. This confirms the precision in the generation of the signals, and there is consistency in the

frequency-voltage values. Furthermore, the voltage variations, with a 5 V source, have a variation with a maximum error of 0.7%.

4.2. Analysis of the Signal Conditioning Stage

Table 3 shows that the amplified voltage reached values lower than ± 19 V with a variation error of less than 1.2%. Furthermore, the intensity control had a variation of 95 levels, with a voltage of 4.98 V (with an error of less than 0.6%). Furthermore, the current protection stage limited the current to 147.6 mA.

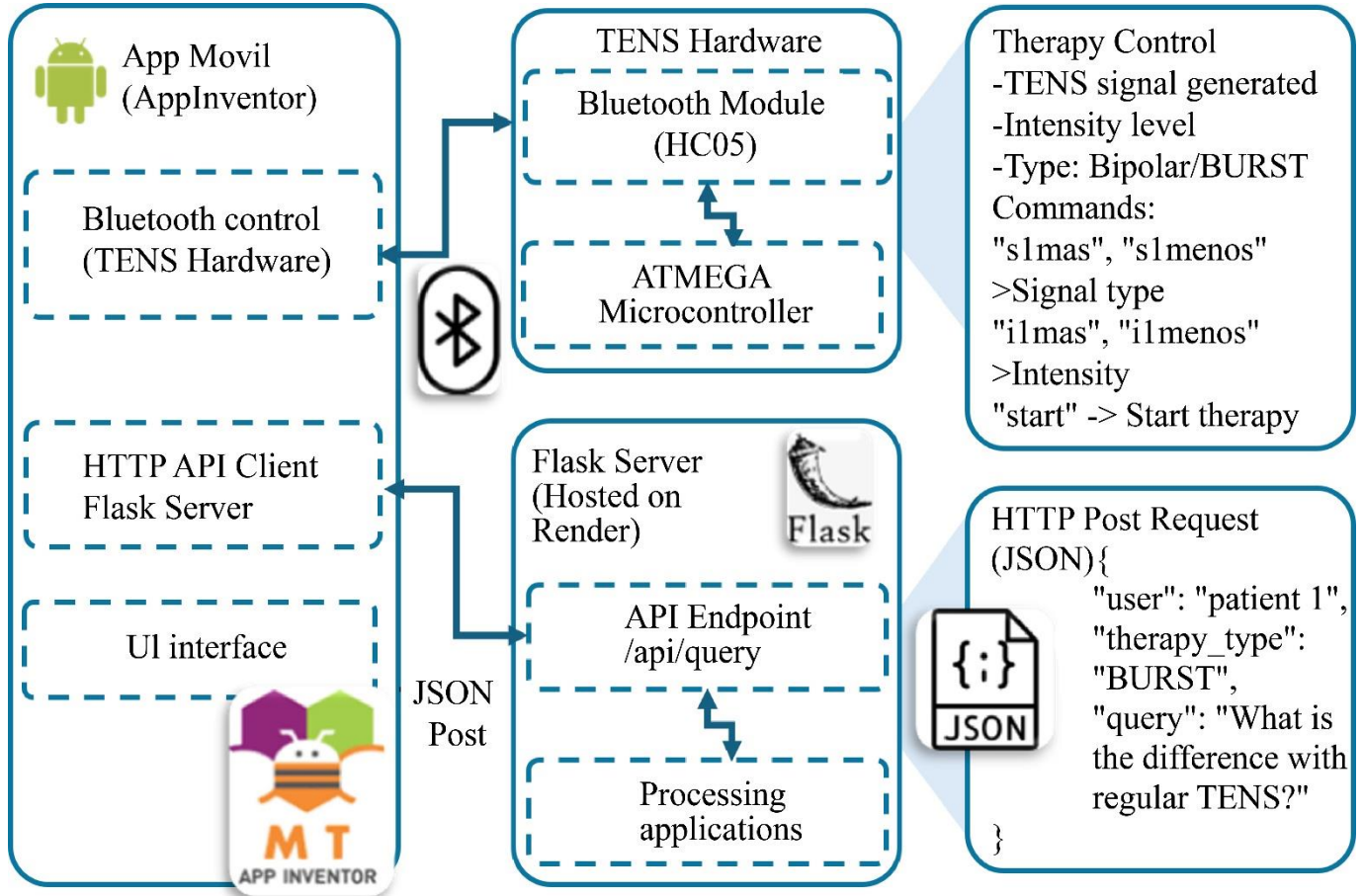


Fig. 7 Interaction of TENS hardware and flask server

Table 2. Validation of signal parameters in experimental tests

Therapy	T.Frequency (Hz)	Frequency (Hz)	A. Error (Hz)	R.Error (%)	Tolerance (%)
Conventional TENS	100.0	100.0	0.0	0.00%	$\pm 1\%$
Pain Relief PG (NML TNS)	10.0	10.0	0.0	0.00%	$\pm 5\%$
BURST Muscle Relaxation	3.0	3.0	0.0	0.00%	$\pm 5\%$

Table 3. Metrics the conditioning stage

Metric	Theoretical Value	Measured Value	Absolute Error	Relative Error (%)
Amplified Positive Voltage	+18.0 V	+18.0 V	0.0 V	0.00%
Amplified Negative Voltage	-18.0 V	-17.8 V	0.2 V	1.11%
Number of Intensity Levels	95	95	0	0.00%
Voltage at Maximum Intensity Level	5.00 V	4.98 V	0.02 V	0.40%
Maximum Allowed Current	150 mA	147.6 mA	2.4 mA	1.6%
Estimated Response Time	-	0.2 s	-	-

4.3. Vectorization Results

Documents on therapeutic processes, technical manuals, and patient treatment guides were processed using LLamaIndex. These documents are shown in Figure 8 in relation to the generated fragments. The fragments were segmented into different numbers, and it was observed that the technical manuals had more fragments with greater amounts of information, despite their small number compared to the other information sources.

4.4. Agent RAG

The LLM RAG agent was evaluated by comparing it with results from manual access to technical documents, obtaining data on response times. In this case, this procedure allowed for quantitative results on semantic accuracy. Furthermore, response times for the test were within 2 seconds, considering tests with three documents (Figure 9)

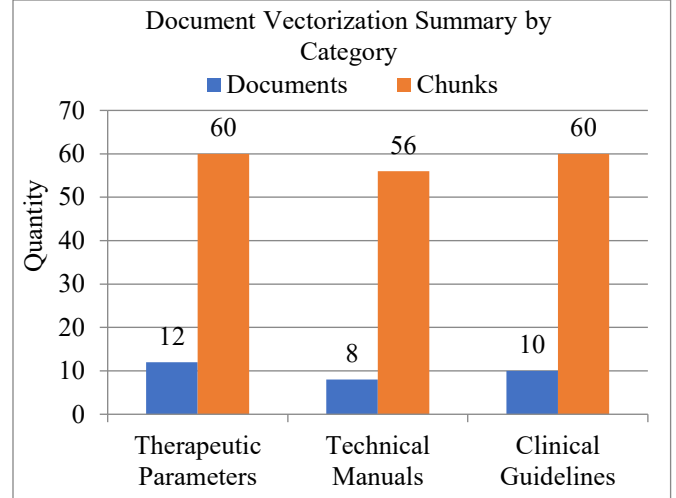


Fig. 8 Document vectorization summary by category

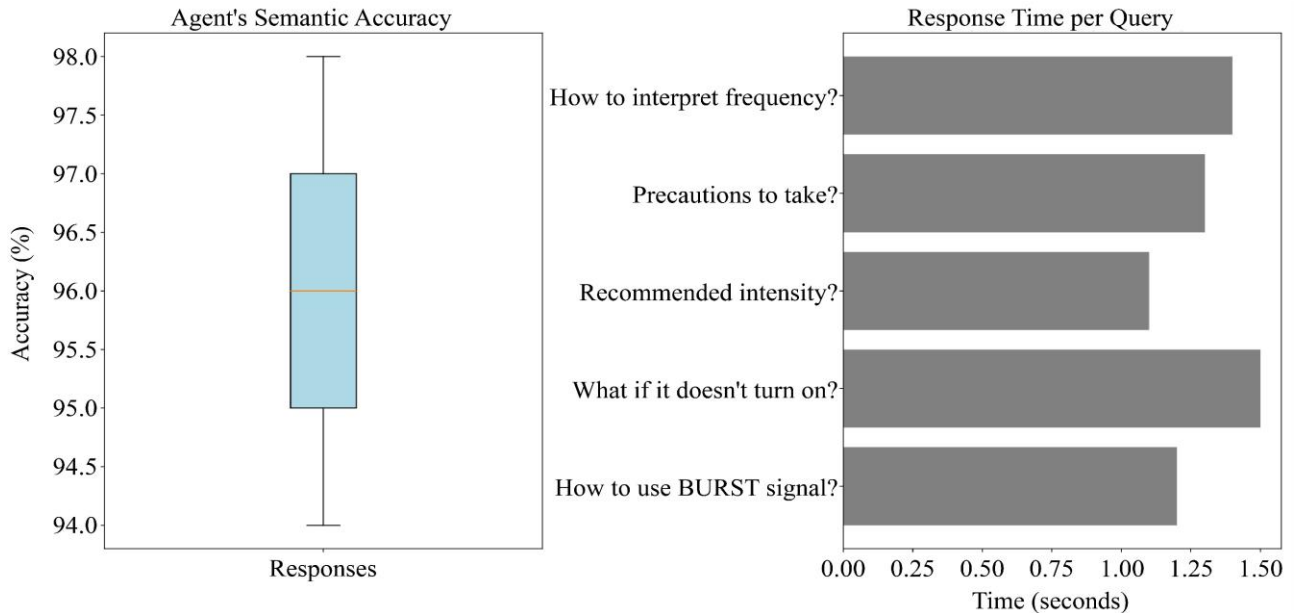


Fig. 9 RAG agent response time and response accuracy

4.5. Agent Web Service and Mobile Interaction

The web service was implemented in the mobile application, where the RAG agent is configured and evaluation metrics are recorded. In addition, the communication behavior with the HC-05 hardware was evaluated with tests at different distances (Figure 10). Figure 11 shows how the Bluetooth signal strength decreased from -33 dBm (0 meters) to less than -87 dBm at 10 meters. The data transmission rate dropped from 100% to 60% at 10 meters.

Figure 12 provides a visual representation of the user experience, where the distribution around the mean, with minimal long tails, indicates that users can generally expect a quick response with a low response time of 3.2 seconds. This validates the RAG agent's processing, highlighting the system's responsiveness.

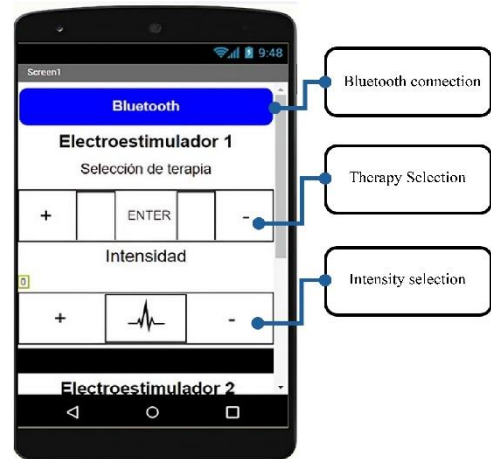


Fig. 10 Control interface in mobile application

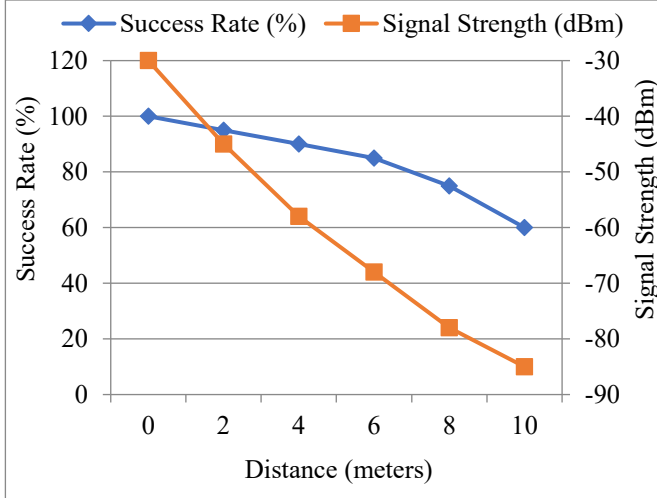


Fig. 11 Bluetooth communication performance with distance

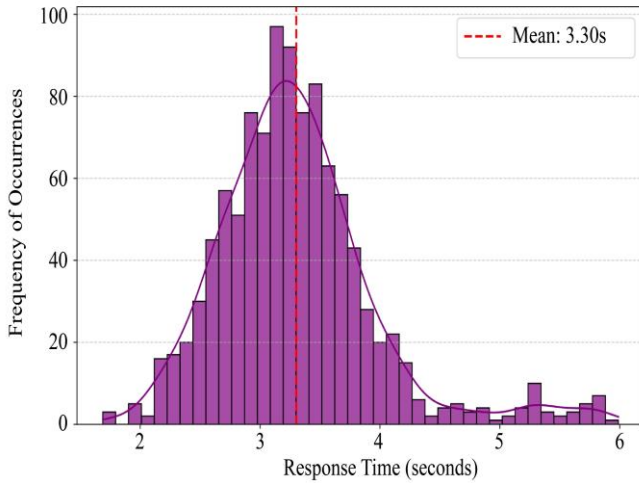


Fig. 12 Distribution of End-to-End response times (mobile app to agent response)

The average interaction time of 3.2 seconds (T_{total}) is distributed between the mobile application processing (JSON generation and sending to the Flask server), the Augmented Retrieval (RAG) process, and the Generation.

$$T_{total} = T_{App} + T_{RAG} + T_{LLM_Gen} \quad (1)$$

The variables in the equation are:

- Mobile Application Processing Time (T_{App}): Average time of 150 ± 30 milliseconds (ms) for serializing the query and sending the HTTP request in JSON format to the Flask server.
- RAG Processing Time (T_{RAG}): The average time for vectorizing the query, performing a similarity search in the database of 170 snippets, and selecting the $k=5$ most relevant snippets is 950 ± 120 ms.
- LLM Generation Time (T_{LLM_Gen}): Processing the LLM and generating the response. The average generation time is approximately 2100 ± 250 ms.

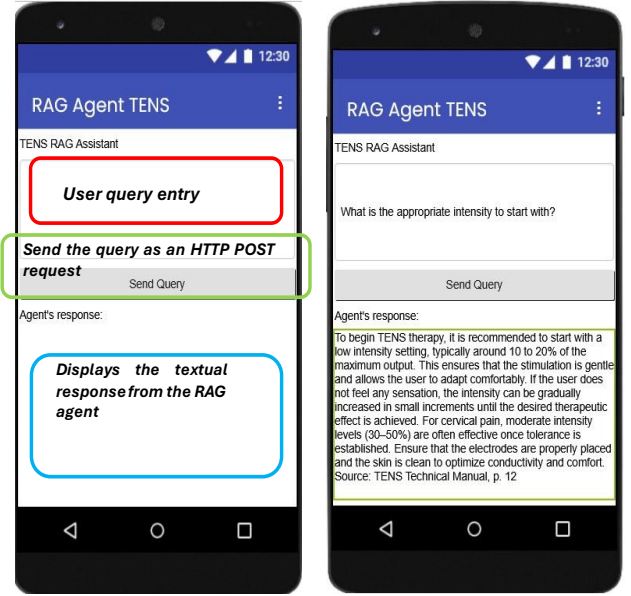


Fig. 13 Responses to the RAG agent from the mobile application

The interaction between the mobile app and the LLM-RAG agent was validated, allowing the user to submit queries related to the use of the TENS device. Upon typing a question and pressing the "Submit" button, the app generated a JSON file that included the query text, user type, and the current therapy parameters. The Flask server receives the data request through the RAG agent, and this response is displayed on the mobile app screen.

The results obtained are considered adequate for remote monitoring processes with information response times of less than 6 seconds. Furthermore, in the case of the reliability of the RAG agent, this was obtained by comparing the responses generated by the RAG with those obtained from technical manuals or databases through manual inspection (obtaining between 93% and 98%, for which the `load_evaluator` function of the `LanChain` tool was used)

The TENS prototype allowed the use of electronic hardware for signal generation, connecting it to the LLM-RAG mobile app. This combination of technologies allowed for monitoring the cervical pain treatment process during remote work. Furthermore, the fulfillment of the objectives was validated, considering that the therapy signals had frequencies within the error limits for this type of application ($\pm 1\%$ and $\pm 5\%$). Furthermore, measurements demonstrated the functioning of the inversion and coupling circuits, with voltage symmetry close to ideal (± 18 V). Digital intensity control allowed 95 levels to be distinguished with high precision.

5. Conclusion

The TENS system successfully integrated electronic hardware for signal generation and conditioning, along with a digital platform combining a mobile app, an LLM-RAG agent,

and web services, validating monitoring and assistance for the treatment of cervical pain during teleworking. The experimental results confirmed the achievement of the objectives set for personalized health applications. Therapeutic signals were generated with frequencies obtained within the established error margins ($\pm 1\%$ and $\pm 5\%$). Furthermore, measurements demonstrated the functioning of the inversion and coupling circuits, with voltage symmetry close to ideal (± 18 V). Digital intensity control allowed 95 levels to be distinguished with high precision.

Furthermore, the document database was structured by processing 30 documents, generating more than 170 fragments per chunk, and vectorized using LlamaIndex. This allowed the agent to respond to queries contextually, with semantic accuracy between 94% and 98%. Furthermore, in the case of the mobile application, its web service communication was verified for communication using the client-server architecture with the RAG agent. Furthermore, the total interaction time (including processing by the RAG agent) was less than 3.2 seconds on average.

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