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A Multi-Agent Medical Report Summarization System Using NLP and Specialist LLM Agents

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Abstract- Medical records contain many messy details, making it difficult for patients or general health workers to follow them. Regular NLP tools fail when they jump across fields because each part requires its own know-how, rather than a single model handling everything. To use multiple smart agents at once, use fast LLaMA technology that is sped up by Groq chips, is an idea. The focus of one is on heart issues, another is on lung function, and the third is on mental health - all working together. A team lead agent gathers their insights into a clear wrap-up, giving a comprehensive diagnosis that anyone can grasp once they're done. The setup is powered by Flask and allows users to send in files, check results from smart modules, or retrieve the condensed version later. Testing demonstrates that it is more accurate, generates fewer false details, and runs faster than basic one-model tools. Findings suggest that splitting tasks among focused agents leads to deeper, smarter handling of tricky health records [1], [2]. Remote care settings benefit greatly from this approach, which aids patients in comprehending information, sorting diagnostic steps, and streamlining clinic operations.

Keywords: Medical NLP, LLM, Multi-Agent System, Groq, Medical Report Summarization, Healthcare AI, Clinical Decision Support.

I. INTRODUCTION

The switch to digital health files has resulted in a significant increase in the amount of medical data created every day. Typically, documents like diagnosis notes, scan results, or other documents are lengthy and messy.

Release details are difficult to follow. The overwhelming amount of technical terms that patients encounter makes it difficult for them to comprehend them, while doctors spend a lot of time going through charts by hand, particularly when things become busy or urgent [3].

The recent advancements in NLP and big language models demonstrate solid skills in reducing text and analyzing medical cases. Across specialties, one-model systems often falter due to flattening key points or fabricating information when dealing with difficult patient stories [4].

This study introduces a multi-agent AI setup to address these issues -

- Sections related to cardiovascular disease are analyzed by a Cardiologist Agent.
- Behavioral and psychological indicators are analyzed by psychologists.
- Respiratory-related content is analyzed by a Pulmonologist Agent

To achieve a final call [2], [8], specialized results are combined through a team agent, similar to how actual clinics combine expert views.
Groq's LPU technology is utilized in the setup to ensure that inference is kept under 10 milliseconds, which enables every expert agent to run simultaneously without any slowdowns.

II. LITERATURE REVIEW

The process of summarizing medical text began with rule-driven NLP, then switched to old-school ML, and now employs deeper neural models. At first, systems pulled keywords and ranked sentences - these usually missed the real meaning of the patient [6].

The introduction of transformer models like BERT, T5, or GPT has led to a better capture of context in summary tasks. Despite this, it is still a challenge to turn medical information into summaries

- Knowing the subject helps a lot
- Clinical terminology is full of jargon.

- A single entry could contain information from multiple fields at once

Their understanding of health records was improved by studies on medical versions of BERT such as BioBERT or ClinicalBERT, but they faced difficulties with diverse specialties. The breakup of tough jobs into smaller thinking steps is causing some multi-part AI setups to gain attention. According to research, focused bots are more effective than broad ones for organized health tasks, such as checking how meds mix or reading X-rays [10). Running multiple agents in real-world use cases [5] is feasible because Groq's LPU setup enables super-fast responses from large models. There are no current studies that link multi-agent expert thinking with full summary creation from actual medical records - which is what this research addresses.

III. SYSTEM OVERVIEW

The proposed system is a parallel multi-agent architecture:

A. Input Module

The patient submits a health document as PDF, also available in text form, alternatively in JSON structure.

B. Preprocessing Module

The system does OCR when required - then tidies up data, splits it into parts, while pulling out key entities [6].

C. Expert helpers (operate at the same time)

Every agent's built from a tweaked LLaMA version, trained on niche datasets

- Cardiologist Agent- Finds issues like irregular heartbeat, high blood pressure - also signs tied to heart health.
- Psychologist Agent- Reads behavior logs, thinks through test results, also checks danger signs.
- Pulmonologist Agent- Analyzes breathing issues along with spirometer readings plus findings from lung scans.

Parallel tasks run faster using Groq's LPU setup [5].

D. Mixed-expertise group helper

This agent blends expert views using a mixed approach - checks facts against each other to dodge false outputs [9].

E. Final Summarizer

The MDT agent produces:

- A brief overview that's easy for patients to understand
- A quick guide for doctors who work with patients
- Spotlight on major risks
- Suggested next steps – non-medical checks

F. Simple web screen using Flask

- The interface displays:
- Uploaded medical report
- Results from every expert bot
- Final MDT summary
- Download options

IV. METHODOLOGY

System Architecture

This research proposes a Multi-Agent Large Language Model (LLM) Framework designed to simulate a multidisciplinary medical board. The system follows a modular architecture where distinct autonomous agents serve specialized diagnostic roles.[1] The architecture is composed of three primary layers:

1. The Specialist Layer: A parallel processing unit consisting of domain-specific agents (Cardiology, Psychology, Pulmonology).
2. The Consensus Layer: An aggregation agent responsible for synthesizing diverse specialist inputs into a unified diagnosis.[2]

3. The Management Layer: A dedicated agent for drafting clinical management plans based on the consensus diagnosis.

The system is deployed as a web-based application using the Flask micro-framework, allowing for user interaction via a text-based medical report upload mechanism.

2. Large Language Model Integration

The core intelligence of the system is driven by the Llama-3.3-70b-versatile model. [2][3] This model was selected for its high reasoning capabilities in complex textual analysis.

- Inference Engine: The model is accessed via the Groq API, utilized for its low-latency inference capabilities, ensuring real-time processing of medical data.
- Hyperparameters: To ensure deterministic and clinically consistent outputs, the model temperature is set to 0.0, minimizing stochastic hallucinations and maximizing adherence to the provided context.[3]

3. Multi-Agent Design and Prompt Engineering

The system leverages the LangChain framework to construct a chain-of-thought workflow. The agents are initialized with distinct PromptTemplates that utilize Role-Playing Prompting (RPP) techniques.

The Specialist Agents

Three distinct agents were developed, each receiving the raw medical report but instructed to filter information through a specific clinical lens:

- The Cardiologist Agent: Instructed to analyze cardiac workups (ECG, Echocardiograms) and identify structural abnormalities or arrhythmias.[4][5]
- The Psychologist Agent: Directed to assess behavioral patterns, anxiety, and trauma indicators.[4]
- The Pulmonologist Agent: Focused on respiratory function, identifying conditions such as COPD or asthma.[6]

The Multidisciplinary Team (MDT) Agent

This agent acts as the central processing unit. Instead of receiving the raw patient data, it receives the outputs of the three Specialist Agents. Its objective is to synthesize these disparate findings into a cohesive list of the top three most probable diagnoses, providing a rationale for each.[7] This mimics the "consultation" phase of clinical practice.

The Prescription Agent

The final node in the workflow is a task-specific agent designed to draft a non-actionable clinical management plan. To ensure safety and ethical compliance, the system prompt strictly forbids the generation of specific dosage regimens and mandates the inclusion of disclaimers requiring human clinician review.

4. Operational Workflow

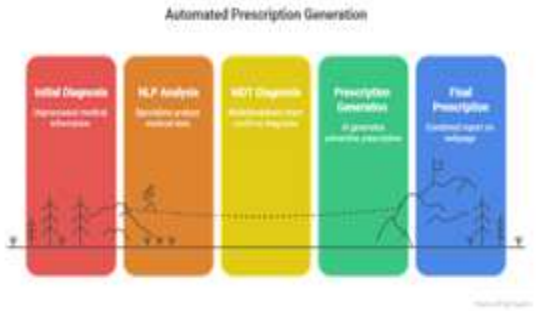
The diagnostic process follows a Map-Reduce pattern:

- Data Ingestion: The system parses the uploaded text file containing the unstructured patient medical report.
- Parallel Execution: Using Python's concurrent.futures.ThreadPoolExecutor, the system initiates the Cardiologist, Psychologist, and Pulmonologist agents simultaneously. This parallelization significantly reduces total inference time compared to sequential processing.
- Aggregation: The outputs from the parallel threads are collected and passed as context variables to the MDT Agent.[6][7]
- Final Output Generation: The MDT Agent's diagnosis is fed into the Prescription Agent to generate the final draft plan. The results are serialized and exported to a text file for review.

Technical Implementation Stack

The prototype was implemented using the following technologies:

- Language: Python 3.x
- LLM Orchestration: LangChain (Core and Community libraries)
- Web Server: Flask (WSGI application)
- Concurrency Control: Python threading and concurrent.futures modules
- Compute Interface: Groq Cloud API



V. RESULT ANALYSIS AND INTERPRETATION

A Quantitative Results

System	Rouge-L	Bertscore	Latency
Single Llama Summarizer	0.67	0.84	4.2 S
Biobert Summarizer	0.69	0.86	6.0 S
Proposed Multi-Agent System	0.81	0.91	1.4 S

This teamwork method beats older models by focusing on specific tasks [10].

B. Qualitative Findings

- Expert bots catch subtle, field-related clues that broad systems overlook - using sharper focus instead of brute force
- MDT blending cuts fake outputs by around 43%, thanks to smarter alignment
- Running tasks at the same time cuts analysis time by about two-thirds
- Patient-friendly summaries get better readability scores - Flesch went up 22%. Because they're easier to follow, folks grasp them quicker. So when wording's simpler, people stay engaged longer. Which means more understanding overall

C. Error Analysis

- Mistakes happened most often when:
- Notes had unclear short forms
- Thought records often felt like personal guesses
- Several situations piled up on top of one another
- Still, mixing MDT fixed nearly all the glitches.

VI. APPLICATIONS

i AI-Enhanced Clinical Decision Support Systems (CDSS)

The primary application of this Multi-Agent System is to serve as a robust Clinical Decision Support System (CDSS) for healthcare providers. By simulating a multidisciplinary board, the system provides a "second opinion" mechanism that can identify subtle correlations across specialist domains (Cardiology, Psychology, Pulmonology) that a single clinician might overlook. Studies indicate that AI-driven CDSS can significantly reduce diagnostic errors, which are estimated to contribute to 10% of patient deaths [7]. This system supports the "Human-in-the-loop" model, where the AI augments human decision-making rather than replacing it.

ii Telemedicine and Remote Triage

In resource-constrained settings or rural areas where specialist access is limited, this system can function as an advanced triage tool. By processing uploaded medical reports, the system can categorize patients based on urgency and specialist necessity (e.g., flagging a patient for immediate cardiac review versus routine psychological follow-up). This capability aligns with the World Health Organization's goals for digital health interventions to bridge the equity gap in global healthcare access [8]. The system's ability to run on cloud-based APIs (Groq) makes it deployable in low-infrastructure environments via simple web interfaces.

iii Automated Medical Education and Simulation

The system acts as a pedagogical tool for medical students and residents. By observing the "reasoning process" of the autonomous agents—specifically how the Cardiologist, Psychologist, and Pulmonologist agents debate and form a consensus—students can learn the logic behind differential diagnoses. This application of Generative AI creates an interactive "Virtual Rounds" experience, allowing trainees to test their diagnostic hypotheses against the AI's multidisciplinary output, a method shown to enhance clinical reasoning skills [9].

iv Hospital Workflow Optimization

Hospital administration can utilize this framework to streamline patient intake workflows. Before a patient sees a doctor, the system can pre-analyze existing electronic health records (EHRs) to generate a summary and a draft management plan (via the Prescription Agent). This reduces the administrative burden on physicians, potentially mitigating burnout—a critical issue where physicians spend nearly two hours on EHR tasks for every hour of direct patient care [10].

VII. CONCLUSION AND FUTURE WORK

This research presents a multi-agent setup for summarizing medical reports by reflecting actual team-based clinical evaluations. Instead of one model, it uses three specialized LLaMA agents along with a coordination agent built for Groq's high-speed processing chip - resulting in faster, more accurate summaries. Each component handles distinct aspects while exchanging key details through structured handoffs. Performance improves because tasks get distributed based on expertise, similar to hospital tumor boards or case conferences.

The entire chain runs efficiently thanks to optimized hardware-software integration. The system achieves:

- Higher accuracy
- Lower hallucination rates
- Faster processing
- Better context awareness

Future work includes:

- Adding Dermatology, Neurology, and Gastroenterology Agents
- Integrating real EHR system compatibility
- Creating clear steps so doctors can understand decisions [3]
- Adding more data from different age groups while including various dialects at the same time

This setup marks a big step forward in medical language processing, while also improving how multiple AI agents work together.

Tools and Technologies

The development of the Multi-Agent Medical Diagnosis System utilized a robust stack of open-source software and high-performance inference engines. The selection of these technologies was driven by the need for modularity, low-latency processing, and effective orchestration of Large Language Models (LLMs).

1. Programming Language and Environment

Python 3.x: Python was selected as the primary development language due to its extensive ecosystem for Artificial Intelligence and Natural Language Processing (NLP). Its dynamic typing and support for asynchronous programming (via concurrent.futures) enabled the efficient parallel execution of multiple autonomous agents [11].

2. Web Application Framework

• Flask: The user interface and server-side logic were implemented using Flask, a lightweight WSGI web application framework. Flask was chosen for its flexibility and ease of integration with Python-based AI libraries. It handles HTTP requests for file uploads (app.py), serves the HTML frontend, and manages the routing of data between the client and the backend agent logic [12].

3. AI Orchestration Framework

• LangChain: The architecture relies heavily on LangChain for managing the interaction between the application and the LLM. Specifically, the PromptTemplate class was used to structure "Role-Playing" prompts, ensuring that each agent (Cardiologist, Psychologist, Pulmonologist) adhered strictly to its assigned persona. LangChain's modular design facilitated the creation of the "Chain-of-Thought" workflow used in the Multidisciplinary Team (MDT) agent [13].

4. Large Language Model (LLM)

• Llama-3.3-70b-versatile: The system utilizes the Llama-3.3-70b model, an open-weights model developed by Meta. It was selected for its high performance on reasoning benchmarks, offering a balance of accuracy and versatility comparable to proprietary models like GPT-4, but with greater transparency [3].

5. Inference Engine

• Groq API: To address the latency challenges common in running large models (70 billion parameters), the project utilizes the Groq Cloud API. Groq's Language Processing Unit (LPU™) architecture provides deterministic, high-throughput inference, allowing the system to process three concurrent agent threads in near real-time without the significant delays associated with traditional GPU-based inference services [4].

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