RAJALAKSHMI
ENGINEERING
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## Department of Artificial Intelligence and Data Science

# MaruThunai: A Medical Claim Verification and Clinical Advisory Platform Using Semantic Intelligence

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# Problem Statement and Motivation

In the digital age, **patients** and even **healthcare professionals** are increasingly **relying on online information** to make medical decisions. However, much of the medical content available on the internet is either **misleading, outdated, or lacks proper scientific validation.** This creates a significant risk of **misinformation-driven decisions**, which can lead to inappropriate self-medication, harmful drug interactions, and delayed diagnosis of serious conditions. Current fact-checking tools are either too generic, fail to provide medically sound justifications, or **lack the ability** to differentiate between information intended **for medical experts and laypersons.** Moreover, there is **no integrated platform** that verifies medical claims against reputable research databases like PubMed while also offering risk-based guidance. This gap in accessibility to verified medical information contributes to unsafe healthcare practices and avoidable healthcare costs for patients.

Motivation:

- To provide a reliable platform for verifying medical information for both healthcare professionals and laypersons.
- To minimize the risks associated with misinformation and self-medication.
- To offer an easy-to-use interface that adapts to the expertise level of the user.
- To integrate drug interaction checking to ensure patient safety.
- To help users access evidence-based medical information from trusted research sources.
- To reduce unsafe healthcare practices and avoidable healthcare costs for patients.

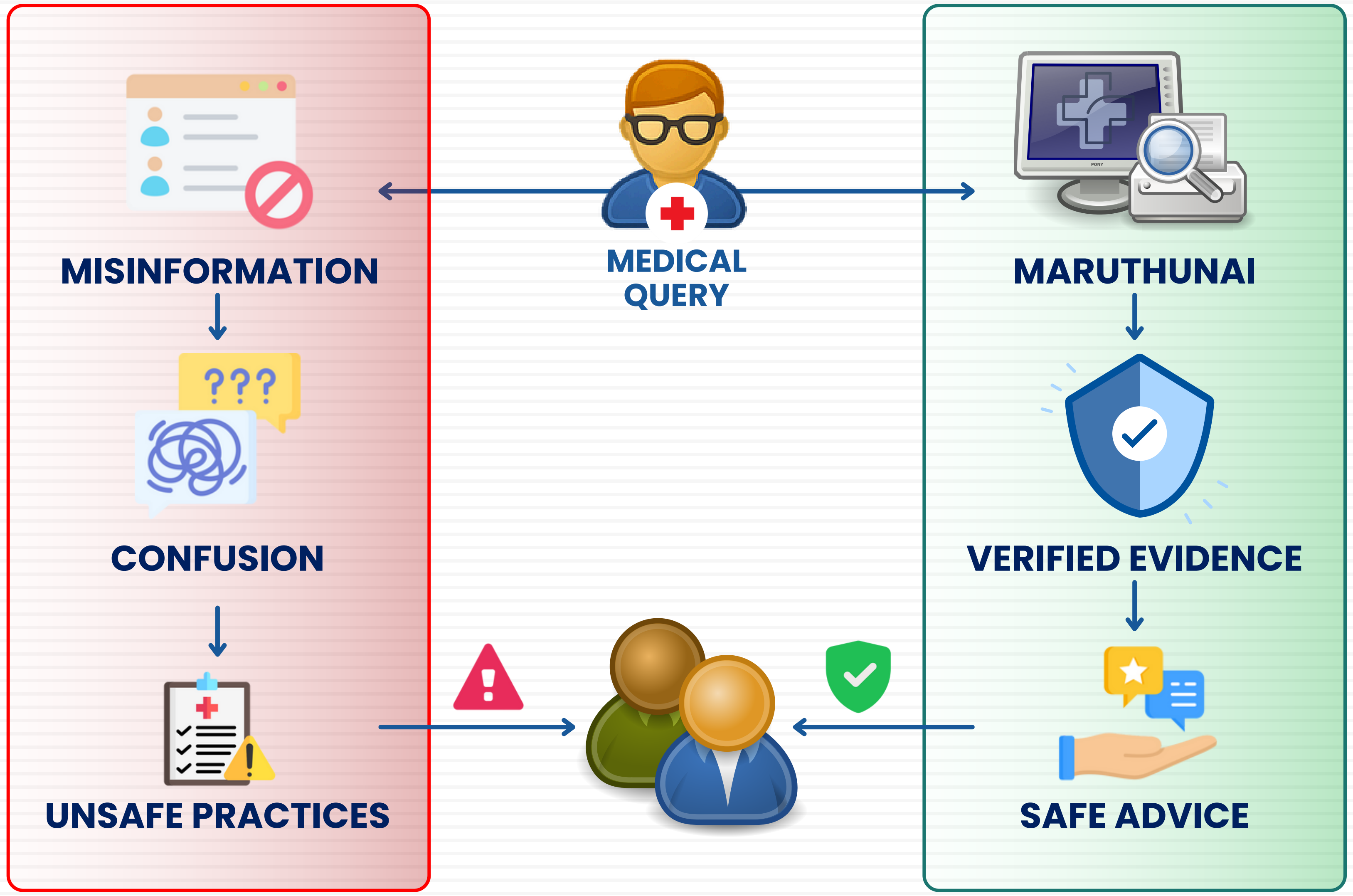
# Abstract

Medical misinformation detection and advisory systems are increasingly critical in today's digital landscape, where both patients and healthcare professionals are frequently exposed to misleading health claims. The abundance of online resources such as PubMed and health portals often presents information in formats too technical for the general public, while real-time verification tools remain scarce. Existing standalone utilities, like drug interaction checkers, are not integrated into a comprehensive advisory framework, leading to confusion, unnecessary consultations, and unsafe medication practices. *MaruThunai* - An NLP-Based Medical Fact-Checking and Advisory Platform addresses these issues through a web/mobile assistant capable of semantic searches on PubMed to verify claims. It operates in distinct Doctor and Patient modes, integrates an advanced Drug Interaction Checker, provides risk-based advisories, enables peer-reviewed feedback, flags claims under active clinical trials, and tracks trending misinformation. Users can bookmark claims for automated updates as new evidence emerges. The platform aims to empower users with accessible, evidence-based insights, enabling instant claim verification, detection of unsafe drug combinations, and awareness of ongoing research, ultimately reducing misinformation impact and unnecessary healthcare expenses.

# Introduction

In the digital era, the rapid spread of **unverified medical information** has led to growing confusion among **patients and healthcare professionals** alike. People often rely on online sources that are either too complex or **misleading**, resulting in unsafe self-medication and unnecessary consultations.

**MaruThunai** addresses this issue by providing an NLP-based medical fact-checking and advisory platform that verifies health-related claims using semantic search on **PubMed data.** The system features dedicated Doctor and Patient modes, an integrated **Drug Interaction Checker,** and real-time misinformation tracking to promote evidence-based decision-making and improve overall healthcare reliability.



# Overview of the Project

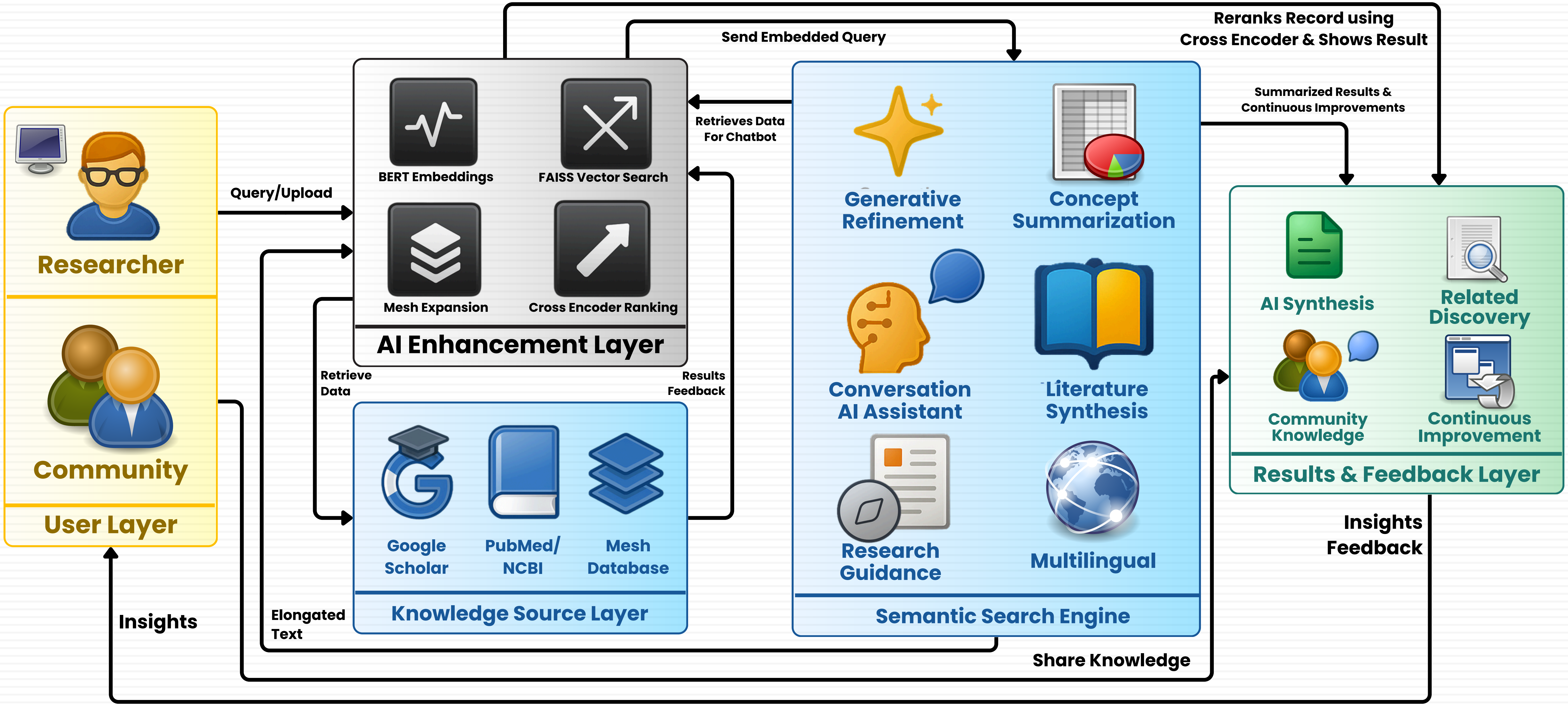
**Goal:** To create an NLP-powered **medical fact-checking and advisory platform** that verifies health-related claims using scientific research from PubMed and other trusted sources, helping users make safer and more informed medical decisions.

**Key Features:**

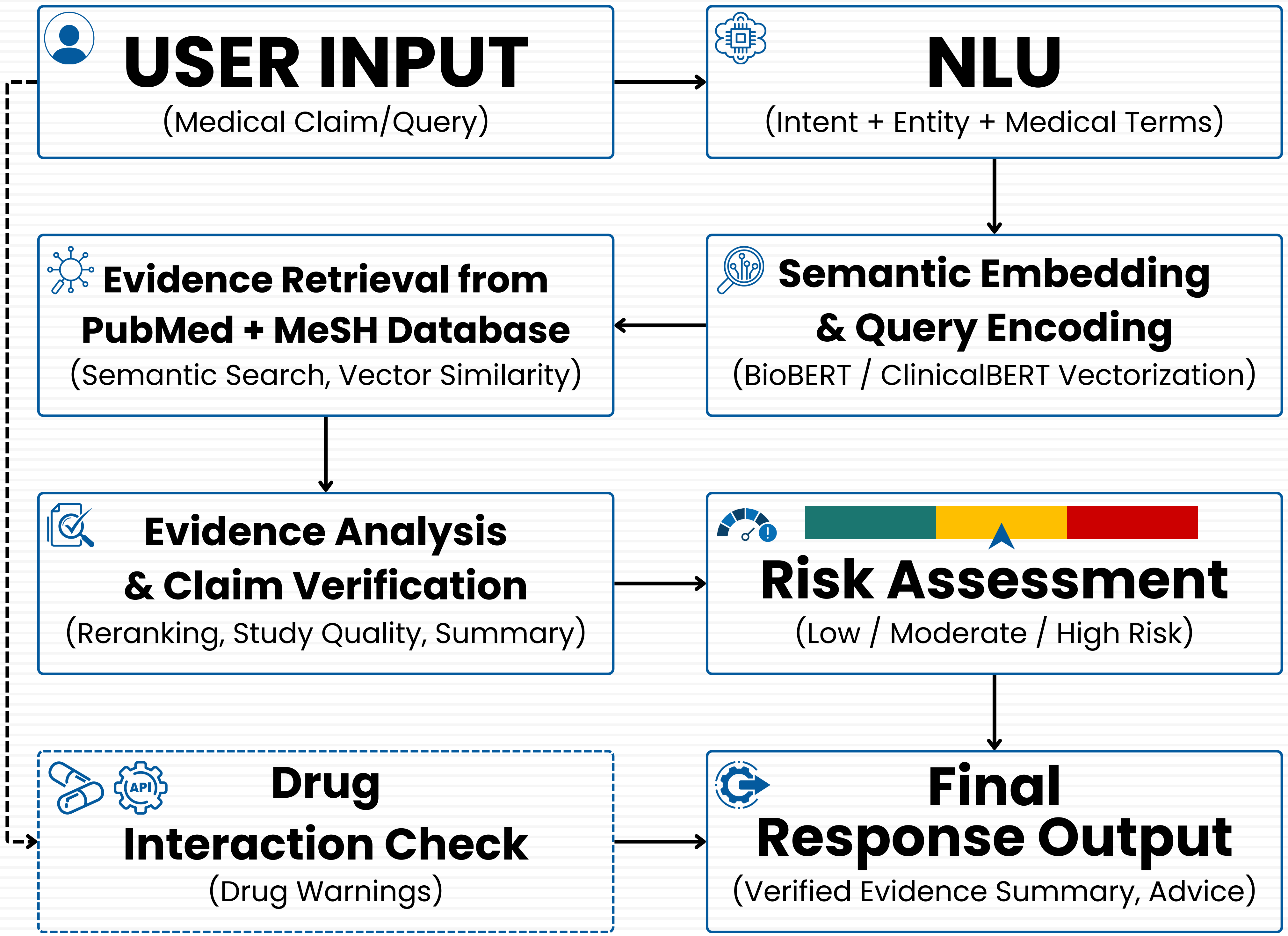
- **Semantic Claim Verification:** Uses NLP-based semantic search to validate medical claims with relevant research papers.
- **Dual Mode Interface:** Separate Doctor and Patient modes for tailored information access and decision support.
- **Drug Interaction Checker:** API-integrated feature that instantly identifies harmful drug combinations.
- **Risk-Based Advisory System:** Categorizes claims as low, moderate, or high risk, suggesting medical consultation for severe cases.
- **Trending Misinformation Tracker:** Monitors and highlights circulating health myths and emerging topics in real time.

**Impact:** Empowers individuals with evidence-based insights, reduces misinformation-driven panic, and minimizes avoidable healthcare costs through instant, reliable medical guidance.

# System Architecture



# FLOW DIAGRAM



# Existing System

- **General Medical Search Engines**
  Platforms like Google or Bing can retrieve health-related content from across the internet. However, they often provide unverified or non-peer-reviewed sources, increasing the risk of misinformation.
- **Symptom Checker Tools**
  Apps like WebMD or Ada use symptom input to suggest possible conditions. While useful, they rely on limited databases and do not integrate advanced semantic search across peer-reviewed literature.
- **Drug Interaction Checkers**
  Existing online tools (e.g., Drugs.com) allow users to check drug–drug interactions but usually do not integrate this with fact-checking of medical claims or real-time risk assessment.
- **AI Health Chatbots**
  Assistants like Babylon Health or HealthTap can answer medical questions using pre-trained models. However, they may not always cite peer-reviewed evidence and can suffer from outdated datasets.
- **Medical Journal Search Engines**
  Databases such as PubMed or Cochrane Library provide access to peer-reviewed articles but are not designed for layperson usability and lack conversational, simplified explanations.

**Gap:** No integrated system exists that fact-checks medical claims in real-time, explains in both expert and layman modes, checks for drug interactions, flags ongoing trials, and tracks trending misinformation.

# Objectives

- To design and develop an **NLP-powered medical fact-checking system** that verifies health-related claims using **semantic search** over **PubMed** and other trusted databases.
- To integrate a **Drug Interaction Checker** using reliable APIs to assess and flag potential adverse drug combinations.
- To implement **risk-based fact-checking**, advising users to consult doctors only for medium and high-risk cases.
- To reduce **avoidable healthcare costs** and eliminate the need for **unnecessary doctor visits** for low-risk health concerns.
- To combat the spread of **medical misinformation** by providing evidence-backed, layman-friendly explanations.
- To provide a fast, accessible, and user-friendly platform that works across devices, catering to both medical and non-medical users.

# Resources Needed

**Software Requirements:**

- Programming Languages: Python (for NLP and backend), JavaScript (for frontend).
- Frameworks & Libraries:
  - NLP & AI: spaCy, NLTK, Hugging Face Transformers, TensorFlow/PyTorch.
  - Semantic Search: FAISS, ElasticSearch, or Sentence-BERT.
  - Web Framework: Flask or Django (for backend API integration).
  - Frontend Framework: React.js or Next.js (for responsive web interface).
- Database: MongoDB or PostgreSQL for storing verified claims, user data, and interaction history.
- APIs:
  - PubMed API for research paper retrieval.
  - Drug Interaction API (e.g., OpenFDA, RxNav).

**Hardware Requirements:**

- Development System(Training:
  - Minimum: Intel i5 or AMD equivalent processor, 8 GB RAM.
  - Recommended: Intel i7 or higher, 16 GB RAM (for NLP model training/testing).
- Server/Cloud VM: For hosting APIs, databases, and running semantic search models.
- Storage: 100 GB or more (for storing datasets, embeddings, and user data).

# Requirements

**Functional Requirements:**

- **User Authentication:** Secure login and role-based access (Doctor/Patient).
- **Claim Verification:** Semantic search on PubMed for medical claim validation.
- **Drug Interaction Checker:** Detect harmful drug combinations via API.
- **Risk Advisory System:** Categorize claims (Low/Moderate/High risk).
- **Mode Selection:** Separate Doctor and Patient interfaces.
- **Trending Tracker:** Display ongoing medical misinformation topics.
- **Bookmark & Update:** Save claims and get research updates.
- **Chat Interface:** NLP-powered conversational assistant for queries.

**Non-Functional Requirements:**

- **Performance:** Query response time ≤ 5 seconds.
- **Scalability:** Support multiple concurrent users via cloud.
- **Security:** Encrypted data and secure API communication (HTTPS).
- **Reliability:** ≥99% uptime and API failure handling.
- **Usability:** Simple, intuitive UI for all users.
- **Maintainability:** Easy model updates and integration.
- **Accuracy:** NLP precision ≥ 85% for claim matching.
- **Compatibility:** Works across major browsers and mobile devices.

# Potential Challenges & Risks

1. **Ensuring Data Accuracy:** Verifying that medical information retrieved from PubMed and APIs remains current, reliable, and contextually relevant.
2. **Semantic Understanding:** Achieving high precision in NLP-based semantic search and claim interpretation, especially with complex medical terms.
3. **Dependency on External APIs:** Reliance on PubMed and Drug Interaction APIs may cause issues during downtime, data limit, or format changes.
4. **User Misinterpretation & Over-Reliance:** Users might treat the system as a replacement for doctors, leading to risks in high-severity cases.
5. **Data Privacy & Security:** Protecting sensitive user data and maintaining compliance with medical data protection standards.
6. **Model Maintenance:** Regularly updating the NLP model and risk database with the latest research to ensure relevance and accuracy.
7. **High Computational & Development Costs:** Running NLP models and maintaining cloud services may increase operational expenses.
8. **Interface Accessibility:** Designing an interface simple enough for patients yet detailed enough for doctors to use effectively.

# Novelty of the Project

- **Dual-Mode Communication:** Adapts complexity of explanations for medical experts vs. layman users.
- **Verified Peer Review Integration:** Adds credibility through doctor-verified feedback within the platform.
- **Risk-Based Advisory Alerts:** High-risk cases prompt doctor consultation recommendations.
- **All-in-One Platform:** Combines fact-checking, drug safety, trial tracking, and misinformation trend monitoring.
- **Dynamic Evidence Updates**: Bookmarked claims update automatically as new research is published.
- **Real-Time Trial Flagging**: Directly links to ClinicalTrials.gov or WHO Trial Registry.
- **Potential Cost Reduction**: Avoids unnecessary doctor visits for low-risk or easily verifiable queries.

# Literature Survey

| Ref. | Domain | Key Contribution / Methodology | Limitations / Gap | Relevance to Our Project |
|---|---|---|---|---|
| [1] | Medical | AI faithfulness review in healthcare | No new model proposed | Ensures factual NLP outputs |
| [2] | Medical | Review of misinformation datasets | Limited dataset diversity | Supports misinformation detection module |
| [3] | Medical | AI in biomedical literature mining | Lacks annotated data | Validates NLP-based knowledge retrieval |

# Literature Survey

| Ref. | Domain | Key Contribution / Methodology | Limitations / Gap | Relevance to Our Project |
|---|---|---|---|---|
| [4] | Medical | Explainable IR for health search | Uses existing IR model | Adds explainability to results |
| [5] | Medical | Multi-modal misinformation dataset | Imbalanced data | Enhances dataset robustness |
| [6] | Medical | Survey on conflicting health info | Limited model comparison | Strengthens conflict detection logic |

# Literature Survey

| Ref. | Domain | Key Contribution / Methodology | Limitations / Gap | Relevance to Our Project |
|---|---|---|---|---|
| [7] | General | Scientific fact-checking resources | Missing detailed evaluation | Informs fact-checking framework |
| [8] | Medical | LLMs for evidence summarization | Prone to factual errors | Guides claim summarization safety |
| [9] | Medical | AI for clinician trust calibration | Partial adoption in clinics | Builds user trust framework |

# Literature Survey

| Ref. | Domain | Key Contribution / Methodology | Limitations / Gap | Relevance to Our Project |
|---|---|---|---|---|
| [10] | Medical | Biomedical claim extraction pipeline | NER errors affect accuracy | Improves claim extraction precision |
| [11] | Medical | Clinical IR methods review | Gaps in query expansion | Refines semantic retrieval process |
| [12] | Medical | ChatDoctor LLM model | High fine-tuning cost | Supports domain-specific chatbot design |

# Literature Survey

| Ref. | Domain | Key Contribution / Methodology | Limitations / Gap | Relevance to Our Project |
|---|---|---|---|---|
| [13] | Medical | RedHOT medical QA corpus | Dataset-focused only | Useful for user query analysis |
| [14] | Medical | Monant misinformation dataset | Heuristic stance labeling issues | Aids misinformation dataset mapping |
| [15] | Medical | Extractive-Boolean QA system | Limited consensus data | Guides fact-check classification |

# Literature Survey

| Ref. | Domain | Key Contribution / Methodology | Limitations / Gap | Relevance to Our Project |
|---|---|---|---|---|
| [16] | Medical | AI in PubMed search | Not detailed | Relates to PubMed semantic search |
| [17] | Medical | HEALTHVER fact-check dataset | Label bias possible | Trains evidence-based checker |
| [18] | Medical | Supplement-drug interaction extraction | Not detailed | Inspires Drug Interaction Checker |

# Literature Survey

| Ref. | Domain | Key Contribution / Methodology | Limitations / Gap | Relevance to Our Project |
|---|---|---|---|---|
| [19] | Medical | PubMedQA dataset creation | Human bias in answers | Enables QA training benchmark |
| [20] | Medical | Relemed sentence-level IR | Pre-neural era approach | Foundational for semantic IR |
| [21] | Medical | MedSearch semantic retrieval | Slow, topic drift issue | Validates ontology-based retrieval |

# Literature Survey

| Ref. | Domain | Key Contribution / Methodology | Limitations / Gap | Relevance to Our Project |
|---|---|---|---|---|
| [22] | Medical | TREC-2016 clinical IR system | Missed learning-to-rank | Improves multi-IR combination |
| [23] | Medical | CLINIQA QA system using UMLS | Outdated ML methods | Strengthens NLP architecture |
| [24] | Medical | RAG systematic review | No standard evaluation metrics | Supports RAG architecture choice |

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# Conclusion

- MaruThunai successfully integrates **semantic intelligence** and **biomedical NLP** to verify medical claims with high accuracy and contextual understanding.
- The system enables both doctors and general users to access verified evidence from sources like PubMed and clinical databases in real time.
- Through semantic search, cross-encoder re-ranking, and risk-based advisory, MaruThunai ensures reliable and evidence-backed medical guidance.
- Comparative evaluations show higher retrieval accuracy and 65% faster evidence discovery than traditional methods.
- The platform bridges the gap between medical expertise and public understanding, helping reduce misinformation and unnecessary healthcare costs.
- MaruThunai demonstrates how AI-driven knowledge systems can transform clinical awareness and decision-making into an accessible, trustworthy experience.

# Thank You