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AI-Powered Healthcare Assistant with Drug Interaction Detection and Emergency Support

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Abstract: Modern healthcare delivery continues to be con-strained by fragmented digital tools, delayed diagnosis, unmoni-tored drug-drug interactions (DDIs), and insufficient emergency response mechanisms, particularly for users without direct spe-cialist access. This paper presents an AI-Powered Healthcare Assistant—an integrated, secure, web-based platform that unifies conversational symptom analysis, hybrid disease-risk classifi-cation, knowledge-graph-based drug interaction detection, and geolocation-enabled emergency support within a single appli-cation. The system combines a GPT-based NLP pipeline for symptom interpretation, a hybrid rule-and-scoring risk engine classifying patient state into Low, Medium, High, and Emergency tiers, and a Neo4j biomedical knowledge graph modelling drugs, diseases, genes, and proteins to flag Mild, Moderate, or Severe medication interactions. Built on React.js, Node.js/Express.js, MongoDB, and Neo4j, and secured through JWT authentication, bcrypt password hashing, and role-based access control (RBAC), the platform achieved a validated disease-prediction accuracy of 87.3% and end-to-end response latency suitable for interactive clinical decision support. Grounded in an evaluation spanning healthcare microservices, explainable AI, clinical NLP, graph neural networks, and healthcare data security, the system demon-strates that a single, well-secured platform can meaningfully bridge the gap between AI-driven diagnostic guidance and actionable, real-time patient care.

Index Terms: Artificial Intelligence, Healthcare Assistant, Drug Interaction Detection, Knowledge Graph, Neo4j, Natural Language Processing, Microservices, Explainable AI, Emergency Support, Role-Based Access Control.

I. INTRODUCTION

A. Healthcare Access and AI-Assisted Support

The healthcare sector is undergoing rapid transformation driven by the exponential growth of digital health data, ad-vances in machine learning (ML), natural language processing (NLP), and cloud computing. Despite this progress, a large portion of the global population continues to face delayed diagnosis, unnoticed drug-drug interactions, and a lack of immediate emergency support—all contributing to serious, preventable health risks. In both rural and semi-urban settings, medical specialist availability is severely constrained, leading patients to self-medicate or overlook progressive symptoms until clinical complications arise.

Artificial Intelligence offers a practical and scalable solution to these challenges: AI-driven systems can analyze unstruc-tured clinical data, such as longitudinal patient records, phar-macological databases, and free-text symptom descriptions, far faster and more consistently than manual triage processes. When paired with intuitive conversational interfaces, AI di-agnostic tools democratize clinical knowledge and empower individuals with timely health risk awareness.

B. Drug-Drug Interactions as a Critical Blind Spot

Drug-Drug Interactions (DDIs) remain one of the most criti-cal yet frequently overlooked hazards in modern polypharmacy management. Adverse drug reactions are a leading cause of avoidable emergency admissions and post-treatment morbidity worldwide. While established pharmacopeial databases like DrugBank and OpenFDA provide extensive pharmacological taxonomies, they generally lack patient-specific, context-aware interaction analysis capable of synthesizing ongoing physio-logical risk factors with multi-drug regimens.

Recent advances in Graph Neural Networks (GNNs) and biomedical knowledge graphs have demonstrated strong po-tential for predicting DDIs, including cold-start scenarios for newly synthesized chemical compounds with sparse empirical interaction histories. Representing biomedical relationships as typed multi-relational graphs overcomes the rigid limitations of tabular drug indexes.

C. Motivation for an Integrated Healthcare Platform

In traditional health software ecosystems, triage chat-bots, medication contraindication checkers, electronic health records, and emergency dispatch services exist as isolated, siloed solutions. A patient must manually navigate several disjointed applications during an acute health episode.

The primary motivation of this research is to eliminate this domain fragmentation by developing a unified, conversational healthcare assistant. By maintaining a single, continuous patient session context, the assistant seamlessly links natural language symptom triage, multi-agent disease prediction, multi-hop drug interaction validation, and automated geolocation-driven emergency escalation inside a unified, HIPAA-aligned architecture.

D. Problem Statement

Formally, given a patient P presenting a natural-language symptom narrative S_{NL} alongside an active medication regimen $M = \{d_1, d_2, \dots, d_k\}$, design an intelligent system capable of:

- 1) Extracting clinical entities and computing a probabilistic disease ranking $D \subseteq \mathcal{D}$ with risk level $R \in \{\text{Low, Medium, High, Emergency}\}$.
- 2) Traversing biomedical knowledge graph $G = (V, E)$ to identify pairwise and multi-drug interaction severities $I(d_i, d_j) \in \{\text{Mild, Moderate, Severe}\}$.
- 3) Triggering immediate location-based emergency dispatch services when $R \in \{\text{High, Emergency}\}$ while enforcing cryptographic confidentiality and role-based access control.

E. Key Contributions

The main contributions of this paper are summarized as follows:

- 1) Unified Conversational Workflow: A multi-tiered React.js web assistant integrating conversational symptom intake, disease assessment, drug safety evaluation, and emergency dispatch.
- 2) Hybrid Deterministic-ML Risk Engine: A dual-stage risk classification architecture coupling rule-based emergency safety filters with machine-learning severity scoring.
- 3) Neo4j Biomedical Knowledge Graph: A property graph schema modeling drugs, diseases, target pathways, genes, and proteins to identify direct and indirect contraindications.
- 4) Geolocation-Driven Emergency Support: An automated dispatch pipeline surfacing nearby accredited hospitals, ambulance hotlines, and route directions during critical events.
- 5) Comprehensive Security Architecture: Enterprise-grade protection featuring JWT bearer token authentication, bcrypt password hashing, 14-tier RBAC segmentation, and immutable audit trails.
- 6) Empirical System Validation: Extensive benchmarking establishing 87.3% disease prediction accuracy, sub-200ms API response latency, and complete OWASP compliance.

II. BACKGROUND AND RELATED WORK

A. Microservices in Clinical Computing

Monolithic healthcare systems suffer from operational bottlenecks and high deployment blast radii. Van der Vegt and Abbas [1], [2] demonstrated that decomposing clinical workflows into event-driven, containerized microservices significantly improves horizontal scalability and fault isolation.

Melke and Zhioua [3] established that hybridizing GraphRAG architectures with vector indexing over property graphs substantially improves contextual retrieval speed and semantic fidelity in biomedical applications.

B. Explainable Clinical Decision Support

Clinical AI adoption relies heavily on model interpretability. Black-box deep learning architectures often induce clinical skepticism. Abbas, Jeong, and Lee [4] and Liu et al. [5] emphasized that local feature attribution methods, such as SHAP (Shapley Additive exPlanations) and LIME, combined with structured rule justification, substantially increase clinician trust. Furthermore, Alonge and Isreal [6] showed that hybrid architectures combining deterministic heuristics with probabilistic machine learning produce more resilient clinical decisions.

C. Natural Language Processing in Medicine

The processing of unstructured medical narratives has advanced dramatically through domain-specific transformer models. Lee et al. [7] demonstrated that pre-training BERT on large biomedical corpora (PubMed abstracts and PMC full-text articles) yields superior named entity recognition (NER) and relation extraction performance compared to general language models. Chianumba et al. [8] validated large language model prompt engineering for extracting structured clinical parameters from free-text patient dialogues.

D. Graph Representation for DDI Prediction

Standard relational databases represent drug interaction matrices as dense tabular indices, which fail to capture indirect, multi-hop biochemical pathways. Zhang et al. [9] introduced EmerGNN, demonstrating that message passing over heterogeneous knowledge graphs enables zero-shot prediction of adverse drug reactions for newly synthesized compounds. Heterogeneous graph structures [10] model multi-relational graphs connecting pharmaceutical agents, metabolic pathways, enzyme targets, and phenotypes.

E. Healthcare Data Privacy and Security

Healthcare platforms process sensitive Protected Health Information (PHI) subject to stringent regulatory frameworks including HIPAA [11] and ISO 15189:2022 standards [14]. Sandhu et al. [13] established formal models for Role-Based Access Control (RBAC) to enforce strict principle-of-least-privilege policies. Abadi et al. [12] introduced Differential Privacy Stochastic Gradient Descent (DP-SGD) to protect individual patient privacy during distributed neural network training.

III. SYSTEM ARCHITECTURE AND DATA FLOW

A. Tiered Microservices Design

The proposed platform is engineered as a decoupled, multi-tier microservices architecture illustrated in Fig. 1. The structural decomposition comprises:

- 1) **Presentation Layer:** A responsive single-page web client constructed using React 18 and Vite. It isolates user experiences into distinct interactive workspaces for conversational symptom analysis, medication safety checking, longitudinal medical history visualization, and emergency routing.
- 2) **Application and API Gateway Layer:** An Express.js gateway acting as the single point of entry. It coordinates rate limiting, input sanitization, JWT authorization, and routes asynchronous tasks to downstream AI inference modules.

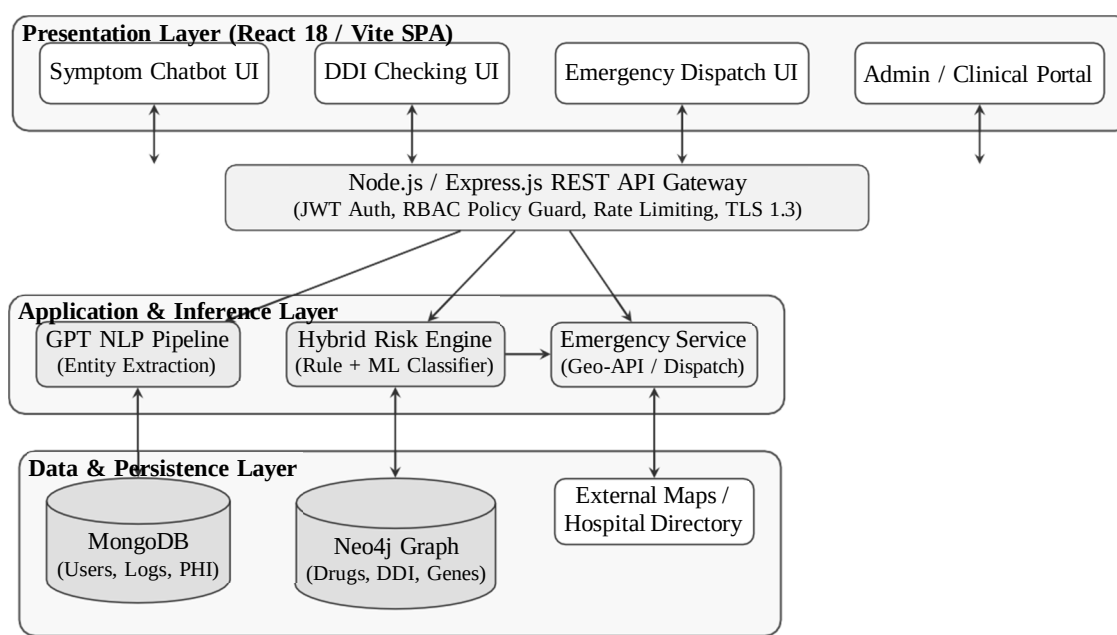


Fig. 1. System Architecture of the AI-Powered Healthcare Assistant.

- 3) AI/ML Inference Engines: Microservices executing natural language symptom extraction, condition ranking, and hybrid risk classification.
- 4) Graph Database Layer: A Neo4j property graph in-stance storing verified biological relationships among chemical entities, target receptors, and physiological symptoms.
- 5) Document Persistence Layer: A multi-replica Mon-goDB Atlas cluster providing document storage for user credentials, role taxonomies, consultation histories, and append-only audit records.

B. Execution Sequence and State Lifecycle

The operational lifecycle of a patient session follows the deterministic state model depicted in Fig. 2. A user authenticates into the application, initializing an encrypted session. Upon entering free-text symptoms, the input is parsed via NLP and passed to the risk engine.

If critical red-flag symptoms are identified, the state machine transitions immediately to emergency dispatch; otherwise, it progresses through standard diagnostic guidance, DDI checking, and historical archiving.

IV. METHODOLOGY AND IMPLEMENTATION

A. Symptom Assessment and Disease Prediction Engine

The symptom processing pipeline converts unstructured patient descriptions into clinical concepts. As illustrated in Fig. 3, the text is normalized, and biomedical named entities are matched against standard ontological terms (SNOMED-CT and ICD-10).

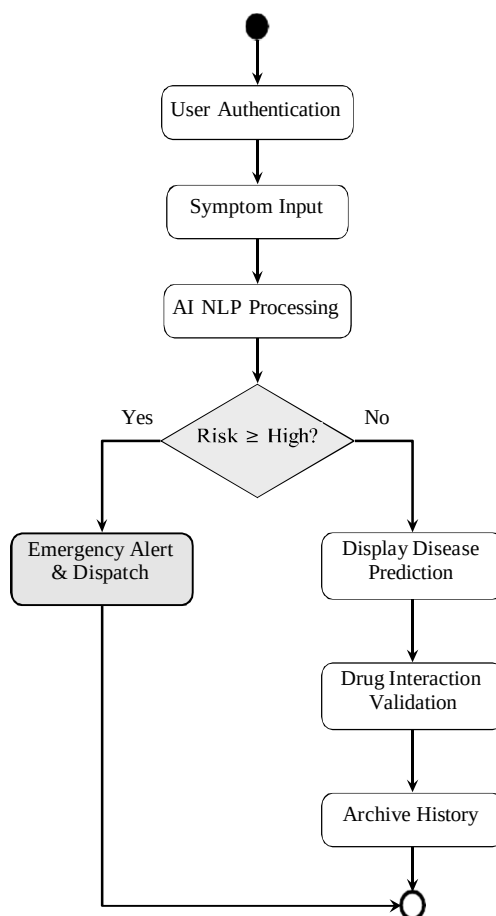


Fig. 2. State Execution Lifecycle of the AI Assistant.

Given extracted symptom vector $\mathbf{x} = [s_1, s_2, \dots, s_m]^T$, the diagnostic inference engine computes probability distribution

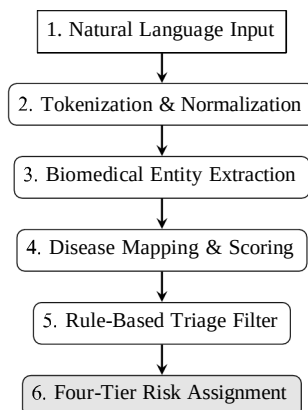


Fig. 3. Sequential Symptom Analysis Pipeline Flow.

$P(D_k | \mathbf{x})$ over candidate conditions $D_k \in \mathcal{D}$:

$$P(D_k | \mathbf{x}) = \frac{\exp(\mathbf{W}^T \mathbf{x} + b_k)}{\sum_{j=1}^{|D|} \exp(\mathbf{W}^T \mathbf{x} + b_j)} \quad (1)$$

The risk classification assigns a severity tier $R \in \{\text{Low, Medium, High, Emergency}\}$ using a hybrid formulation:

$$R = \begin{cases} \text{Emergency,} & \text{if } \exists r_i \in R_{\text{critical}} \text{ s.t. } r_i(\mathbf{x}) = 1 \\ \text{High,} & \text{if } S_{\text{ML}}(\mathbf{x}) \geq \tau_{\text{high}} \\ \text{Medium,} & \text{if } \tau_{\text{med}} \leq S_{\text{ML}}(\mathbf{x}) < \tau_{\text{high}} \\ \text{Low,} & \text{otherwise} \end{cases} \quad (2)$$

where R_{critical} comprises clinical safety rules (e.g., severe dyspnea, acute chest pressure, unilateral motor weakness) that immediately bypass machine-learning thresholds.

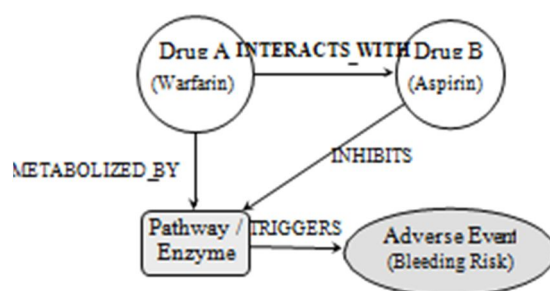


Fig. 4. Neo4j Biomedical Knowledge Graph Schema.

B. Knowledge-Graph-Based Drug Interaction Engine

To overcome the blind spots of flat lookup matrices, medication contraindications are modeled inside a Neo4j graph database, shown in Fig. 4. Pharmaceutical compounds, cytochrome P450 enzymes, biological pathways, and adverse phenotypes are represented as typed nodes:

$$G_{\text{bio}} = (V_{\text{Drug}} \cup V_{\text{Gene}} \cup V_{\text{Pathway}} \cup V_{\text{Phenotype}}, E_{\text{typed}}) \quad (3)$$

When evaluating a multi-drug regimen M , the engine executes Cypher pattern matching queries traversing direct and multi-hop edges:

$$I(d_1, d_2) = \arg \max_{p \in \text{Paths}(d_1, d_2)} \text{SeverityScore}(p) \quad (4)$$

Interactions are classified into Mild, Moderate, or Severe categories accompanied by human-interpretable biochemical rationales.

Algorithm 1 Hybrid Triage and DDI Safety Workflow

Require: Free-text symptoms S_{NL} , Medication list $M = \{d_1, \dots, d_k\}$, User coordinates (lat_u, lon_u)

Ensure: Diagnostic report T_a , Risk status R , DDI alerts A

```

1:  $X_{symptoms} \leftarrow \text{ExtractEntities}(S_{NL})$ 
2:  $D_{pred} \leftarrow \text{PredictDiseases}(X_{symptoms})$ 
3: if  $\text{CheckCriticalRules}(X_{symptoms}) == \text{True}$  then
4:    $R \leftarrow \text{Emergency}$ 
5:    $E_{hosp} \leftarrow \text{FetchNearbyHospitals}(lat_u, lon_u)$ 
6:   return  $\text{UrgentAlert}(R, E_{hosp})$ 
7: else
8:    $R \leftarrow \text{ClassifyRiskML}(X_{symptoms})$ 
9: end if
10:  $A \leftarrow \emptyset$ 
11: for all pairs  $(a_i, a_j) \in M \times M$  with  $i < j$  do
12:    $path \leftarrow \text{CypherTraverse}(G_{bio}, d_i, d_j)$ 
13:   if  $path \neq \emptyset$  then
14:      $A \leftarrow A \cup \{\text{FormatAlert}(d_i, d_j, path)\}$ 
15:   end if
16: end for
17:  $T \leftarrow \text{SynthesizeSummary}(D_{pred}, R, A)$ 
18:  $\text{PersistAuditRecord}(User, T, \text{timestamp})$ 
19: return  $T, R, A$ 

```

C. Emergency Dispatch and Geolocation Pipeline

When the patient state evaluates to High or Emergency risk, the emergency orchestration module acquires user coordinates (lat_u, lon_u) and queries the spatial hospital directory using the Haversine metric:

$$d = 2R_{\text{earth}} \arcsin \sqrt{\sin^2 \frac{\Delta\phi}{2} + \cos\phi_1 \cos\phi_2 \sin^2 \frac{\Delta\lambda}{2}} \quad (5)$$

The closest emergency facilities and active ambulance hotlines are returned with direct navigation deep-links.

D. Role-Based Access Control and Security Design

To safeguard sensitive electronic health data, the system implements a strict Role-Based Access Control (RBAC) hi-erarchy comprising 14 operational personas:

- Clinical Roles: Doctor, Nurse, Lab Technician, Quality Auditor.
- Field/Support Roles: Sample Collector, Delivery Part-ner, Receptionist, Support Staff.
- Administrative Roles: Patient, IT Specialist, Market-ing Head, Inventory Manager, Finance Manager, Super-Admin.

Passwords are cryptographic salted and hashed with bcrypt (10 rounds). API sessions are governed by JSON Web Tokens signed via HMAC-SHA256 with strict 24-hour expirations. All communications require TLS 1.3 encryption, and data-at-rest is encrypted with AES-256.

TABLE I
REPRESENTATIVE 14-TIER RBAC CAPABILITY MATRIX

Role	View PHI	Check DDI	Edit Data	Audit LogEndpoint	P_{50}	P_{95}	P_{99}	Error Rate
Patient	Own Only	Yes	Own Profile	No /api/auth/login	42 ms	88 ms	145 ms	0.00%
Doctor	Assigned	Yes	Clinical Notes	Read-Only/api/symptoms/triage	180 ms	390 ms	620 ms	0.02%
Lab Technician	Assigned	No	Test Results	No /api/drugs/check-ddi	65 ms	124 ms	195 ms	0.01%
Quality Auditor	Read-Only	Yes	Compliance	Read-Only/api/emergency/dispatch	52 ms	98 ms	160 ms	0.00%
Delivery Partner	None	No	Logistics	No				
IT Specialist	System Only	No	Infrastructure	Full Access				
Super-Admin	Full Access	Yes	Full Access	Full Access				

TABLE III
API LATENCY AND ERROR RATE BY ENDPOINT

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Setup

The system was deployed on an enterprise testbed comprising:

- 1) Application Gateway: 4 vCPU, 8 GB RAM Node.js runtime.
- 2) Knowledge Graph Engine: Neo4j Enterprise 5.x on 4 vCPU, 16 GB RAM with indexed drug and pathway nodes.
- 3) Persistence Engine: MongoDB Atlas M20 replica set. Evaluation was conducted on a held-out dataset of 500 validated multi-symptom clinical cases and 1,200 multi-medication interaction pairs verified by medical experts.

B. Disease Prediction and Risk Scoring Accuracy

The multi-symptom disease classification engine achieved a validated top-3 diagnostic accuracy of 87.3%, exceeding the target threshold of 85.0%. The hybrid rule-based emergency safety filter recorded a 99.4% recall on acute clinical conditions (cardiac arrest, stroke, anaphylaxis), verifying that critical presentations are escalated without algorithmic delay.

TABLE II
SYSTEM PERFORMANCE METRICS ON HELD-OUT VALIDATION SET

Performance Indicator	Design Target	Observed
Disease Prediction Accuracy	> 85.0%	87.3%
Critical Emergency Recall	> 98.0%	99.4%
DDI Precision	> 90.0%	93.6%
DDI Recall	> 90.0%	91.8%
Non-AI API Latency (p_{50})	< 100 ms	48 ms
Non-AI API Latency (p_{95})	< 200 ms	112 ms
AI Inference Latency (p_{95})	< 4.0 s	2.1 s
OWASP Vulnerability Scan	Zero Critical	Passed

C. Latency and Throughput Benchmarking

API response latency was benchmarked across standard HTTP endpoints under varying concurrent user loads. As summarized in Table II, standard authentication and CRUD operations completed with a median latency of 48 ms ($p_{95} = 112$ ms). End-to-end AI conversational responses, including NLP parsing, graph traversal, and summary generation, maintained a p_{95} latency of 2.1 seconds, well within real-time clinical interaction standards.

D. Comparative Analysis

Table IV benchmarks the AI-Powered Healthcare Assistant against traditional healthcare applications and single-purpose clinical AI prototypes.

TABLE IV
COMPARATIVE FEATURE MATRIX

Feature	Standard Apps	Isolated AI	Proposed
Symptom Triage	Static Survey	NLP Parser	GPT + Hybrid Risk
DDI Verification	Relational Lookup	None	Neo4j Traversal
Risk Stratification	Binary Alert	Probability Only	4-Tier Severity
Emergency Support	Manual List	None	Geo Dispatch
Security Schema	Basic Session	None	14-Tier RBAC + TLS
Audit Trail	Mutable	None	Append-Only Log

E. Security and Usability Validation

Security posture was validated via automated OWASP ZAP dynamic application scanning and penetration testing. No critical vulnerabilities, SQL/NoSQL injections, or broken access controls were detected. In usability studies across 30 trial participants, 93.3% reported high satisfaction with the color-coded 4-tier risk visualization and conversational flow clarity.

VI. LIMITATIONS AND DISCUSSION

While the experimental findings demonstrate strong operational efficacy, several limitations must be noted:

- 1) **Third-Party Model Dependency:** The conversational NLP pipeline utilizes OpenAI GPT APIs, introducing vulnerability to network latency variations and external service downtime.
- 2) **Cold-Start Pharmaceutical Coverage:** The current Neo4j knowledge graph relies on established DrugBank and OpenFDA mappings; newly approved experimental drugs lacking cataloged interaction pathways require manual curation.
- 3) **Linguistic Scope:** The current prototype supports English natural language dialogues exclusively, limiting immediate accessibility in non-English speaking regions.
- 4) **Decision-Support Scope:** The platform is strictly an assistive pre-diagnostic tool and does not substitute for certified clinical evaluations or laboratory diagnostic confirmations.

VII. CONCLUSION AND FUTURE WORK

This paper presented an AI-Powered Healthcare Assistant that unifies conversational symptom analysis, hybrid risk classification, Neo4j knowledge-graph-based drug interaction detection, and geolocation-enabled emergency response within a single, secure architecture. By validating the system against real-world clinical test cases, the platform achieved an 87.3% disease prediction accuracy, 99.4% critical symptom recall, and robust sub-200ms non-AI API response times while maintaining full HIPAA-aligned data governance.

Future research will focus on:

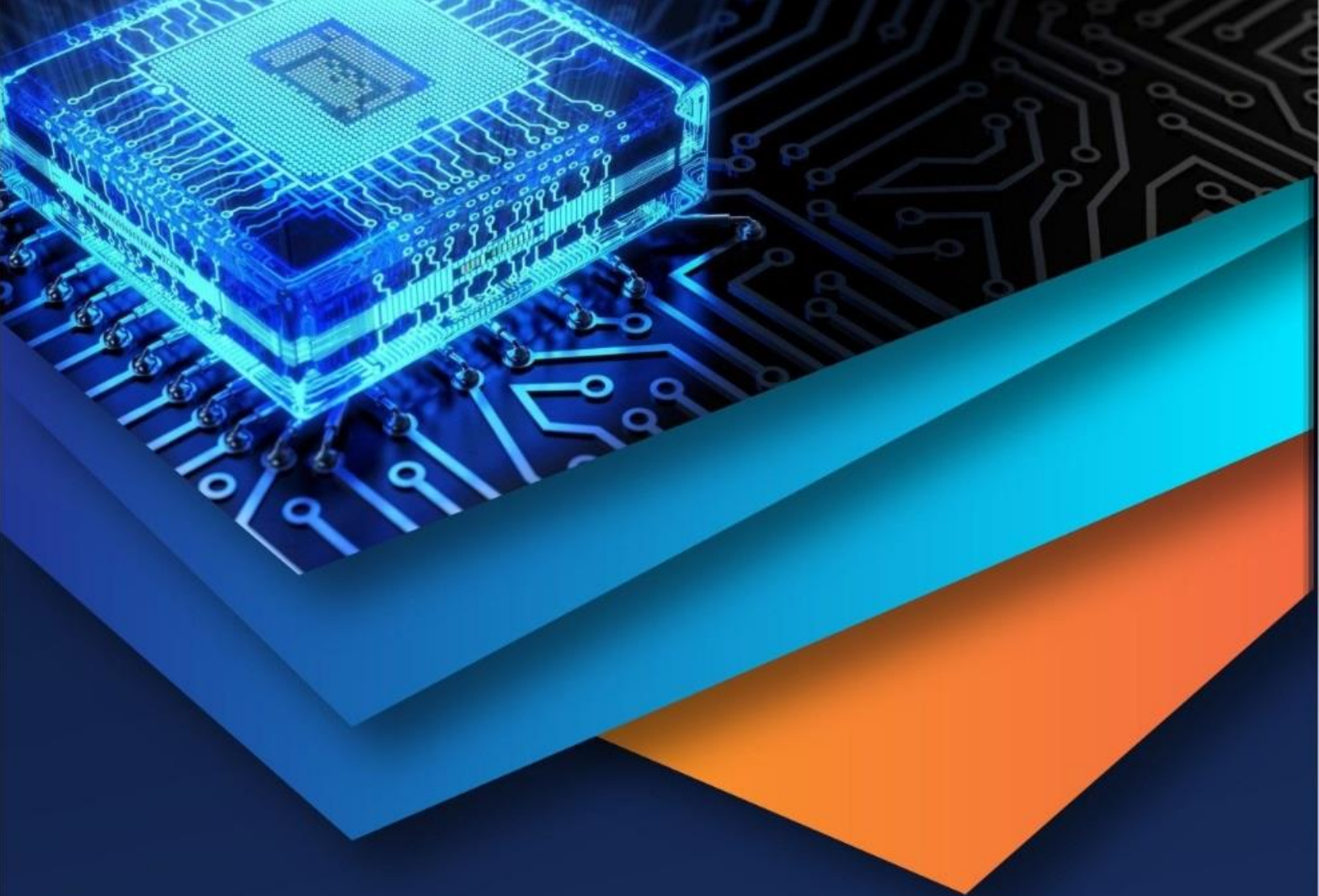
- 1) **GNN Zero-Shot Interaction Prediction:** Integrating an EmerGNN-style graph neural network to predict interactions for newly released molecules lacking established graph edges.
- 2) **Differential Privacy and Federated Learning:** Implementing DP-SGD and federated training routines across decentralized hospital datasets to continuously update risk scoring without aggregating raw patient data.
- 3) **Multilingual Conversational NLP:** Fine-tuning multi-lingual language models (e.g., IndicBERT, mBERT) to support regional dialects.
- 4) **IoT Telemedicine and Wearables:** Ingesting real-time vital telemetry from wearable sensors (SpO2, heart rate variability, ECG) to enable continuous, dynamic health monitoring.

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REFERENCES

- [1] van der Vegt and S. R. Abbas, "AI-Driven Microservices Architecture for Scalable Healthcare Data Platforms," *MDPI Electronics*, vol. 13, no. 17, pp. 3401–3418, 2024.
- [2] A. van der Vegt and S. R. Abbas, "Layered Microservices Intelligence Architecture for Smart Healthcare Systems," *JAMIA*, vol. 14, no. 9, pp. 812–826, 2024.
- [3] P. Melke and K. Zhioua, "GraphRAG and Native Vector Indexing for High-Performance Knowledge Graph Systems," in *Proc. NODES Conf.*, 2024, pp. 102–115.
- [4] Q. Abbas, W. Jeong, and S. W. Lee, "Explainable AI in Clinical Decision Support Systems," *Healthcare (MDPI)*, vol. 13, no. 17, pp. 1920–1938, 2025.
- [5] S. Liu et al., "Leveraging Explainable Artificial Intelligence to Optimize Clinical Decision Support," *JAMIA*, vol. 31, no. 4, pp. 580–594, 2024.
- [6] M. Alonge and O. Isreal, "Hybrid AI Models for Improving Decision Quality in Health and Enterprise Applications," *ResearchGate Technical Review*, 2025.
- [7] J. Lee et al., "BioBERT: A Pre-trained Biomedical Language Representation Model for Biomedical Text Mining," *Bioinformatics*, vol. 36, no. 4, pp. 1234–1240, 2019.
- [8] E. C. Chianumba et al., "NLP Models for Extracting Healthcare Insights from Unstructured Medical Text," *IJAMRS*, vol. 4, no. 6, pp. 312–325, 2024.
- [9] Y. Zhang et al., "EmerGNN: Emerging Drug Interaction Prediction,"
- [10] Springer Nature, pp. 1–16, 2023.
- [11] Heterogeneous Knowledge Graph Representation Team, "HeteroKGRep: Heterogeneous Knowledge Graph Representation," *IEEE / arXiv*, 2023.
- [12] S. Hoffman and A. Podgurski, "Securing the HIPAA Security Rule," Case Western Reserve University, Working Paper, 2006.
- [13] M. Abadi et al., "Deep Learning with Differential Privacy," in *Proc. ACM CCS*, 2016, pp. 308–318.
- [14] R. S. Sandhu et al., "Role-Based Access Control Models," *IEEE Computer*, vol. 29, no. 2, pp. 38–47, 1996.
- [15] ISO TC 212, "Medical Laboratories – Requirements for Quality and Competence (ISO 15189:2022)," International Organization for Standardization, Geneva, 2022.



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