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Construction of an Intelligent Early Warning System for a Cloud-Based Laboratory Data Platform under the Medical Consortium Model

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Abstract: With the continuous advancement of the tiered diagnosis and treatment system, the medical consortium model has gained increasing attention as an important approach to promoting the vertical integration of healthcare resources. Within this context, laboratory data, as a key component of healthcare information systems, urgently requires efficient sharing and intelligent analysis. This paper designs and constructs an intelligent early warning system for laboratory data based on a cloud platform tailored to the medical consortium model. Through standardized data formats and unified access interfaces, the system enables the integration and cleaning of laboratory data across multiple healthcare institutions. By combining medical rule sets with machine learning models, the system achieves graded alerts and rapid responses to abnormal key indicators and potential outbreaks of infectious diseases. Practical deployment results demonstrate that the system significantly improves the utilization efficiency of laboratory data, strengthens public health event monitoring, and optimizes inter-institutional collaboration. The paper also discusses challenges encountered during system implementation, such as inconsistent data standards, security and compliance concerns, and model interpretability, and proposes corresponding optimization strategies. These findings provide a reference for the broader application of intelligent medical early warning systems.

Keywords: Medical consortium; Laboratory data; Cloud platform; Intelligent early warning; Data standardization; Machine learning

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1. Introduction

In recent years, as China deepens its healthcare system reforms, the tiered diagnosis and treatment system has gradually taken shape. The medical consortium (MC) model—designed to improve the accessibility of high-quality medical resources and strengthen primary care—has been widely established and promoted across regions. Within this collaborative framework, data sharing and service coordination among different levels of medical

institutions are foundational for achieving efficient diagnosis and resource integration. However, many MCs still face significant challenges in laboratory data acquisition, transmission, storage, and analysis, such as inconsistent data standards, scattered platforms, and severe data silos, all of which hinder dynamic, cross-institutional monitoring and rapid response. Laboratory test results, as highly structured and time-sensitive core medical data, are not only essential in clinical diagnosis but also play a vital role in public health surveillance, infection control, and chronic disease management. Traditional reliance on manual inspections or static rule matching has become insufficient to meet current demands for real-time, accurate, and intelligent data processing—especially in the context of normalized epidemic prevention and frequent infectious disease outbreaks. There is an urgent need to build an integrated system platform that combines data aggregation, intelligent analysis, and automated alerts to enhance emergency responsiveness and medical coordination across the consortium. The rapid development of new-generation information technologies such as cloud computing, big data, and artificial intelligence provides the technical foundation for unified access, efficient processing, and intelligent interpretation of laboratory data within the MC. As a scalable, elastic, and secure infrastructure, cloud platforms have become the backbone of regional healthcare information systems. Intelligent early warning systems, built atop sufficient data accumulation, can leverage both expert rule sets and learning-based models to detect potential risks in a timely manner, thereby significantly improving proactive healthcare capabilities. Based on an in-depth analysis of the MC's operational requirements and the characteristics of laboratory data, this paper proposes and implements an intelligent early warning system based on a cloud platform architecture. The system features cross-institutional data integration, standardized processing pipelines, and a hybrid alert mechanism combining rules and models. Its feasibility and effectiveness have been validated through real-world deployment. This study aims to provide technical support and a replicable roadmap for advancing intelligent risk control and data-driven innovation within medical consortia.

2. Theoretical foundation and related research

2.1. Medical consortium architecture and data collaboration mechanisms

The medical consortium (MC) is a critical organizational model in China's healthcare reform aimed at implementing tiered diagnosis and treatment. Its core objective is to integrate medical resources vertically by linking tertiary hospitals with primary care institutions, forming a collaborative healthcare community. This model facilitates resource sharing, remote consultations, personnel training, and clinical pathway alignment, thereby alleviating difficulties in accessing and affording healthcare. Typical MC configurations include urban medical groups, county-level healthcare alliances, and cross-regional specialty networks. These structures are usually led by tertiary hospitals and connected to lower-tier hospitals and primary care centers (such as community health centers and township clinics). Information systems play a pivotal role in supporting the functioning of MCs; their maturity directly influences the efficiency of collaboration and quality of service delivery [1]. However, challenges persist due to lagging infrastructure, heterogeneous vendor systems, and the lack of unified data standards. Laboratory data, in particular, are both time-sensitive and critical for diagnosis and public health monitoring. Disparities in Laboratory Information Systems (LIS) across institutions—such as inconsistent data structures, coding schemes, and transmission protocols—hinder data interoperability and cross-institutional validation. To address these issues, many MCs have initiated the construction of regional health information platforms or cloud-based data hubs. These platforms standardize access protocols and aggregate key data types such as lab results, imaging, and electronic medical records (EMRs). Technical methods such as API integration, master data management, data de-

identification, and access control have been employed to enable secure data sharing, collaborative services, and remote oversight. Emerging technologies like blockchain, data middleware, and FHIR are also being explored to facilitate more flexible, secure, and intelligent data exchange. In summary, data collaboration mechanisms under the MC model are fundamental to building smart healthcare ecosystems and enabling intelligent early warning systems. A unified and efficient laboratory data cloud platform not only breaks down information silos but also lays a reliable data foundation for downstream predictive analytics and risk modeling [2].

2.2. Development of laboratory data platforms and intelligent early warning systems

Laboratory medicine is a cornerstone of modern clinical care, generating highly structured, frequently updated, and information-rich datasets. As regional healthcare informatization accelerates, centralized management and deep application of laboratory data have become key to improving care quality and operational efficiency. In particular, under the context of MC construction, smart hospitals, and regional health platforms, the need for integrated, standardized, and intelligent laboratory data platforms is more pressing than ever. In both domestic and international settings, the development of laboratory data platforms has evolved from single-institution deployments to region-wide aggregation, and now to centralized cloud-based management [3]. Traditional LIS systems, which focus on internal lab workflow management, are insufficient for large-scale data computation and inter-institutional collaboration. In response, more healthcare providers are adopting cloud computing and big data technologies to build laboratory data cloud platforms that support standardized data ingestion, cleaning, storage, and unified query services. In terms of intelligent early warning, initial systems primarily relied on static thresholds and rule-based alerts—e.g., flagging test values that exceed defined limits or show abnormal trends. While simple and explainable, such methods depend heavily on manual rule definition and struggle to detect complex or latent risk patterns. With the rise of AI and machine learning, researchers have begun training classification, time-series, and deep learning models using historical lab data to predict individual or population-level health risks [4]. Models based on SVM, Random Forest, and XGBoost have shown strong performance in early cancer screening, infectious disease surveillance, and lab quality control. Recent studies have also addressed issues of model interpretability, real-time responsiveness, and cross-domain generalization. Techniques like SHAP (Shapley Additive Explanations) are employed to enhance clinician trust; stream processing frameworks (e.g., Kafka + Flink) are used to improve real-time performance; and transfer learning methods help adapt models to new institutions or populations. Overall, the integration of laboratory data platforms with intelligent early warning systems represents a key direction in the development of smart healthcare. Building a cloud-based platform that supports multi-institutional collaboration and intelligent risk detection is not only a technical challenge in health IT but also a strategic approach to improving disease surveillance and healthcare quality management [5].

3. System architecture design

3.1. Overall cloud platform architecture

Under the medical consortium model, achieving centralized, standardized, and intelligent processing of laboratory data across multiple institutions requires a highly available, scalable, and secure cloud-based architecture. The platform must support data access from heterogeneous systems and multi-tenant management while meeting the demands of real-time processing and intelligent alerting at scale. Accordingly, the laboratory data cloud platform designed in this study adopts a layered, decoupled architecture, comprising four core layers: data ingestion, data

processing, intelligent analysis, and service presentation. This layer handles the collection and standardized transformation of data from various LIS systems across medical institutions [6]. It supports multi-source heterogeneous data integration through standard protocols such as HL7, FHIR, and CDA, with middleware (e.g., Kafka, RabbitMQ) ensuring high-throughput data transmission. Real-time validation and logging mechanisms are implemented to guarantee data accuracy and traceability. Serving as the core of the cloud platform, this layer includes data cleansing, standardization, anonymization, structural mapping, and storage management. A data middleware approach is adopted to unify multi-source indicators and establish a master data management system, enabling the standardized mapping of item names, codes, and units. Data storage combines distributed databases (e.g., HBase, ClickHouse) and object storage (e.g., OSS, S3), supporting both structured queries and batch reads for model training. This layer integrates rule engines and AI models, functioning as the system's risk identification core [7]. On one hand, a built-in rule base (e.g., continuous abnormal infection indicators) supports real-time alerting; on the other, machine learning and deep learning models (e.g., XGBoost, LSTM) are deployed for trend prediction, clustering, and anomaly detection. Models are containerized via Docker and orchestrated in a Kubernetes cluster, enabling elastic scaling and high-concurrency inference. To meet the needs of various user roles (e.g., clinicians, public health regulators, lab quality managers), this layer provides a unified web and mobile visualization portal. It leverages front-end libraries such as ECharts and AntV to present patient test history trends, alert records, and inter-institution comparisons. An RBAC-based permission control system ensures secure and compliant data access. Additionally, the platform adopts a hybrid cloud deployment strategy, with core computing nodes hosted in regional healthcare data centers and edge hospital nodes using lightweight gateways for data synchronization. The system integrates logging, performance monitoring (e.g., Prometheus + Grafana), and operational alerts to ensure high availability and maintainability. In summary, the multi-layer design and integration of critical technology components lay a solid foundation for centralized management and intelligent warning of laboratory data under the medical consortium model, supporting future business expansion and algorithm optimization [8].

3.2. Data standardization and sharing mechanisms

One of the primary challenges in building a unified laboratory data cloud platform within a medical consortium is the inconsistency of data standards. Institutions often use LIS systems from different vendors, resulting in varied formats, inconsistent naming conventions, and incompatible codes, which can cause discrepancies in encoding, units, and data completeness. To enable effective integration and sharing, a robust data standardization and sharing mechanism must be established. Standardization forms the basis for cross-institutional data recognition. The platform adopts a "national standard + custom extension" model, aligning with standards such as the Basic Framework for Electronic Medical Records, the Hospital Information Interoperability Standards, and LOINC codes. Standardization is implemented across three main aspects: Code normalization: A unified code mapping table is created for all test items, prioritizing the use of LOINC and ICD-10 codes. Local codes are assigned to custom items with traceable mappings. Naming and unit standardization: A master data table defines the Chinese/English names, measurement units, reference ranges, and sex/age stratifications to resolve discrepancies in item representations. Structured data cleansing: Incoming data undergoes field mapping, format validation, anomaly detection, and data completion to improve structural integrity and accuracy. The platform adopts a "centralized storage + tiered authorization + anonymized access" strategy to ensure clinical collaboration while safeguarding data security and compliance. Key mechanisms include: Data domain partitioning: Data is categorized by

institution and business type, each with its own access policies. Role-based access control (RBAC): Access to querying, exporting, analytics, and modeling is granted based on institutional identity and user roles. Sensitive fields are anonymized by default and accessible only with explicit authorization. Standardized interfaces and protocols: RESTful APIs and HL7 FHIR-based services are provided, with rate limits and authentication protocols to support downstream systems and multi-system integration. To address the diverse data usage needs of institutions at different levels, the platform supports three typical sharing modes: Horizontal sharing: Institutions of the same tier share test results for regional alert linkage. Vertical sharing: Primary care institutions upload test results for review by higher-tier hospitals, enabling tiered diagnosis and remote consultation. Research sharing: De-identified, aggregated datasets are made available to research teams via sampling and permission auditing, supporting disease studies and AI model development. Through these standardization and sharing mechanisms, the platform addresses issues such as inconsistent data formats, incompatible interfaces, and inadequate sharing within the consortium, laying a solid data foundation for precise modeling and real-time early warning [9].

4. Construction and implementation of the intelligent early warning model

4.1. Risk identification logic and alert rule system

In the context of a medical consortium, where laboratory data is sourced from diverse institutions and systems, the core challenge of an intelligent early warning system is the timely and accurate identification of potential risks. A robust warning system should detect abnormal trends or emergent events early and respond automatically through graded alert mechanisms, supporting clinical decision-making and public health interventions. To meet this goal, this study proposes a hybrid alert logic system that combines medical rules with anomaly detection models. The platform follows a closed-loop path: "data-driven → rules-first → model-assisted → feedback iteration." Initially, expert knowledge and regulatory rules are used to define a static rule base for preliminary alerts. Then, machine learning algorithms identify abnormalities beyond the rule coverage. Finally, expert validation and user feedback refine both rules and models continuously. The rule base forms the system's first line of defense, incorporating clinical guidelines and public health standards, while allowing for custom expansion. Common rule types include: Threshold rules: Alerting when infectious indicators like WBC, CRP, or PCT exceed defined limits. Trend rules: Detecting continuous escalation of a single patient's test values, suggesting clinical deterioration or lab error. Anomaly distribution rules: Identifying local spikes in positivity rates, signaling potential outbreaks. Quality control rules: Flagging deviations across sample batches or abnormal control substances. Cross-indicator rules: For example, elevated ALT and AST with abnormal bilirubin, indicating hepatic injury. Rules can be customized by dimensions such as age, gender, region, and disease type. Priority, sensitivity, and response strategies are also configurable. To enhance clinical applicability, alerts are stratified into three levels based on severity and urgency: Level 1 (Red): Major public health risks or systemic lab errors; automatic notification of administrators and public health authorities. Level 2 (Orange): Potential group abnormalities or worsening trends; review required by lab or clinical personnel within 24 hours. Level 3 (Yellow): Isolated abnormal results; recorded in the system and flagged to responsible staff for review. Alerts are dispatched via LIS/HIS pop-ups, SMS/WeChat, email, or the platform task center, ensuring timely response. By combining domain expertise with data-driven models, the platform achieves explainable, high-performance risk identification while generating labeled data and scenario input for future model training and clinical validation [10].

4.2. Alert levels and response mechanism design

To ensure that the intelligent early warning system not only accurately identifies potential risks but also prompts timely response and intervention from medical personnel, a scientifically grounded alert grading system and an efficient, coordinated response mechanism must be established. Once an alert is triggered, it should enter a unified workflow promptly, enabling risk notification, task assignment, result tracking, and closed-loop processing, thereby enhancing the overall risk control capacity of the medical consortium.

(1) Alert level classification standards

Based on the urgency, potential impact, and clinical severity of events, the system classifies intelligent alerts into three response levels, each with a corresponding workflow:

Level 1 Alert (Red): Major public health emergencies or critical laboratory anomalies

Applicable to situations involving group-level risks or significant public health concerns, such as abnormal clustering of infectious disease markers in a specific region or systemic laboratory failures. The system automatically notifies platform administrators, public health authorities, and relevant clinical experts, requiring manual confirmation and emergency response initiation within one hour.

Level 2 Alert (Orange): Potential group anomalies or worsening trends

Triggered when abnormal results for a particular test item appear concentrated within a certain institution or time period, though not yet meeting mandatory reporting thresholds. The system reminds responsible physicians or lab quality control staff to complete a manual review within 24 hours and suggests whether to escalate the alert level.

Level 3 Alert (Yellow): Individual or isolated abnormal results

Typically used for preliminary identification of single data anomalies, such as a test result slightly exceeding reference ranges. These events are logged and displayed to responsible staff through the platform dashboard or LIS pop-ups without requiring immediate cross-institution coordination.

The system allows flexible adjustment of alert levels based on regional policies or departmental requirements and supports user-defined mapping of rules and severity levels to enhance configurability.

(2) Response workflow and closed-loop task management

Once an alert is triggered at any level, the system automatically generates a task and pushes it to the designated responsible personnel. The response mechanism consists of the following key steps: Task assignment and notification: Based on the alert type and the patient's affiliated institution, the system identifies the corresponding responsible personnel (e.g., lab physicians, attending clinicians, infection control officers) and delivers task notifications via SMS, mobile apps, or the platform dashboard. Manual review and confirmation: The assigned personnel must log into the system within the specified time frame to review the alert, confirming whether it represents a true anomaly or a false alarm caused by sample error, operational mistake, etc. All review outcomes are recorded in the system audit log. Response actions and recommendation generation: The system provides initial suggestions (e.g., retesting, clinical notification, disease control reporting), and allows users to add remarks, upload verification results, or submit additional documentation. Closed-loop tracking: A status dashboard monitors the progress of alert handling. Tasks not resolved within the designated timeframe are escalated to higher-level supervisors to ensure that the entire process remains trackable, accountable, and auditable.

(3) Integration with clinical workflows

The alert response process is seamlessly integrated with clinical workflows through interfaces with

Hospital Information Systems (HIS), Laboratory Information Systems (LIS), and mobile healthcare platforms (e.g., doctor workstations or apps). For instance, when a physician orders a lab test, the system can automatically display the patient's historical alert records; LIS can present pop-up reminders for critical results; and across multiple institutions in the consortium, alerts can be shared and jointly handled via the cloud platform. In addition, the platform supports the generation of periodic alert analysis reports, providing statistical summaries and classification of recent alert events. These insights assist administrators in evaluating the system's effectiveness, identifying inter-institutional quality disparities, and optimizing rule parameters accordingly. By establishing a multi-level, closed-loop response framework, the system enhances the operability and timeliness of alerts, shifts risk management from passive response to proactive intervention, and fully demonstrates the value of intelligent early warning in quality control and public health protection across the medical consortium.

5. Implementation and application case analysis

In the actual deployment of the regional medical consortium in City A, the intelligent early warning system was applied to the monitoring scenario of respiratory infectious diseases, successfully achieving a typical early risk intervention. A certain community health service center continuously uploaded the test results of multiple patients within three days. The system found that the white blood cell (WBC) and C-reactive protein (CRP) showed an abnormal upward trend and were concentrated in the same geographical area. After cross-analysis through the rule engine and the LSTM model, the platform determined it to be "abnormally concentrated distribution," triggering a secondary warning and simultaneously notifying the district disease control center and the infection department of the leading hospital. After intervention and verification by disease control personnel, it was confirmed that there was a mild transmission of influenza A in the area. Subsequently, the community was guided to strengthen prevention and control measures, and antiviral drug resources were allocated. Through the platform's early warning, it only took 48 hours from the abnormal discovery to the intervention and handling of the epidemic, significantly shortening the response time and preventing a large-scale spread. This case demonstrates that the efficient capabilities of the intelligent early warning system in unified data collection, model judgment, and cross-institutional collaboration can provide strong support for public health prevention and control, and also verifies the practicality and promotion value of the system in the medical alliance scenario.

6. Conclusion

This paper focuses on the integration and application of inspection data under the medical consortium model and designs and implements a set of intelligent early warning system based on the cloud platform. The system has achieved abnormal identification and hierarchical response to key inspection indicators through unified data standards, modular platform architecture, and multi-model fusion technology. The pilot results show that the system has a good effect in improving the data collaboration efficiency among multiple institutions, enhancing the timeliness of infectious disease early warning, and strengthening the quality control ability of laboratories. Although there are still challenges in terms of inconsistent data standards, model interpretability and process response mechanisms, through continuous optimization of model algorithms, improvement of permission mechanisms and promotion of institutional embedding, the intelligent early warning system is expected to be widely applied in a wider range of regional medical alliances, helping to build an efficient, safe, and intelligent

regional medical quality supervision system.

Disclosure statement

The author declares no conflict of interest.

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