A Gis-Based Mobile Application for Real-Time Disease Outbreak Monitoring and Prediction in Zambia

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ABSTRACT

Timely and effective response to disease outbreaks remains a persistent challenge, especially in resource-constrained environments such as Zambia. This study presents the development of a GIS-based mobile application that combines Geographic Information Systems (GIS) with artificial intelligence (AI) to enhance real-time outbreak monitoring and decision-making. The system integrates geospatial visualization with AI-driven analytics to identify potential hotspots, predict disease propagation trends, and generate actionable recommendations for public health stakeholders. Built using a full-stack architecture, the application leverages Flutter for the frontend, Firebase for backend services and cloud database, and the DeepSeek & Gemini API for AI-powered qualitative insights. While existing solutions in countries like India and China have shown the potential of merging AI with geospatial analysis for epidemic tracking and agricultural pest management [1], such integration is limited in Zambia's public health landscape. This research addresses that gap through a scalable, mobile-centric solution designed specifically for localized deployment. A qualitative evaluation of the prototype indicates strong potential for improving epidemiological surveillance and informing data-driven interventions in Zambia and similar low-income settings.

Keywords: GIS, disease mapping, outbreak, AI, public health, ICT, mobile application

INTRODUCTION

The increasing frequency and rapid spread of infectious diseases, including emerging zoonotic pathogens, has heightened the demand for advanced epidemiological surveillance tools. In many resource-constrained settings like Zambia, traditional disease surveillance methods are hindered by delayed data reporting, fragmented systems, and lack of spatial intelligence, thereby impeding timely public health interventions.

Geographic Information Systems (GIS) have long been recognized for their role in mapping and visualizing disease dynamics. When combined with Artificial Intelligence (AI), these technologies offer powerful capabilities such as hotspot detection, real-time forecasting, and automated response recommendations [2]. Globally, real-time GIS-AI integration has been implemented in various forms—for instance, during the COVID-19 pandemic in Asia, where AI-powered dashboards enabled regional governments to reduce outbreak response times by over 30% through predictive analytics and automated alerts [3].

In the African context, particularly Zambia, the implementation of digital outbreak management platforms is still in its infancy. Previous local studies have highlighted the viability of AI-based monitoring systems for non-health applications such as locust detection, where lightweight AI models like MobileNet V2 were deployed for accurate identification in rural zones [4]. These findings underscore the feasibility of adapting similar approaches to disease surveillance through mobile-first GIS systems.

Moreover, researchers in Zambia have proposed scalable digital solutions for health centers that integrate data mining and reporting capabilities, emphasizing the need for structured health data workflows that operate efficiently in environments with low computational resources [5]. The current study builds upon these foundations by developing and evaluating a full-stack GIS-based mobile application that unifies geospatial mapping, real-time data ingestion, and AI-assisted analytics tailored for infectious disease outbreaks.

The primary objective of this research is to design an intuitive, scalable, and mobile-optimized

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platform for disease mapping that is applicable to the Zambian healthcare context. This tool aims to empower health professionals with timely insights to inform decisions, allocate resources, and anticipate future disease spread based on structured, location-specific data.

LITERATURE REVIEW

The integration of Geographic Information Systems (GIS) into public health surveillance has been instrumental in understanding disease dynamics across space and time. GIS enables researchers and policymakers to correlate disease spread with geospatial variables such as population density, environmental factors, and transportation networks. It has been extensively applied in the management of cholera, malaria, and influenza to visualize outbreak clusters and guide intervention strategies [6].

Despite its proven utility, traditional GIS platforms often operate in isolation from real-time data sources and predictive analytics. Systems like District Health Information Software 2 (DHIS2), widely adopted across Africa, including Zambia, support national-level data collection but lack real-time integration, spatial analytics, and AI-assisted forecasting [7]. This presents a technological limitation in environments where rapid public health responses are critical.

The application of Artificial Intelligence (AI) in public health surveillance is increasingly recognized as a transformative force. AI techniques such as machine learning, deep learning, and natural language processing (NLP) have enabled early outbreak detection, anomaly detection in case trends, and automated data interpretation [8]. For instance, AI-enabled surveillance platforms deployed during the COVID-19 pandemic demonstrated the value of hybrid models that fuse AI with GIS data to improve prediction accuracy and visualize high-risk zones [9].

In the Zambian context, early work by Halubanza et al. [10] successfully implemented lightweight AI models (MobileNet V2) for locust detection, proving the feasibility of deploying on-device AI for real-time monitoring in remote areas with limited connectivity. Although not designed for human disease, this work offers a technological template for spatially distributed outbreak monitoring.

Additionally, Kebede and Alemayehu [11] documented the use of mobile GIS platforms integrated with AI to support disease surveillance in rural Ethiopia, revealing similar infrastructure and resource constraints. Their model highlighted the importance of optimizing user interfaces for non-technical health personnel and emphasized the need for low-latency AI systems.

Collectively, the literature points to the increasing convergence of GIS, mobile technology, and AI as a critical next step in health informatics. However, there remains a scarcity of fully integrated platforms tailored for low-resource countries that unify real-time data capture, geospatial visualization, and AI-powered forecasting in one system. This study aims to address that gap by developing and evaluating a scalable, cloud-based GIS-AI application specifically designed for outbreak detection and intervention in Zambia.

RESEARCH METHODOLOGY

This research employed an Agile development methodology, enabling iterative design, implementation, and testing of a GIS-based mobile application for disease outbreak surveillance. Agile was chosen due to its flexibility and emphasis on user feedback, which is critical for health applications intended for field deployment in dynamic environments.

The project was executed over a series of structured development sprints, each focused on a specific functional component: data ingestion, geospatial visualization, AI integration, and dashboard analytics. Prior to development, the system architecture was modeled using Unified Modeling Language (UML) tools including an Entity-Relationship Diagram (ERD), a Class Diagram, and an Activity Diagram to capture system behavior and component interactions.

The technology stack was selected to balance performance, scalability, and mobile accessibility:

- Frontend: Developed using Flutter, an open-source mobile SDK, allowing for high-performance cross-platform deployment on both Android and iOS. Its widget-based architecture supported the creation of an intuitive and responsive user interface.

- Backend and Database: Built on Firebase, offering real-time cloud-based data

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storage via Firestore, robust user authentication, and seamless integration with third-party APIs. Firebase was selected for its efficiency in mobile-first architectures and proven use in low-latency data environments [12].

• AI Integration: The system interfaces with the DeepSeek & Gemini API, a third-party service providing AI-generated qualitative analysis. This module receives structured disease case data and returns predictive insights and policy recommendations, which are rendered on the application's dashboard.

Similar cloud-based architectures have been adopted in other AI-health systems, such as those described by Jiang et al. [13], who emphasized the advantages of modular design for deploying AI in resource-constrained health systems.

While the prototype currently relies on an external AI API, efforts are underway to localize the AI component. This approach aligns with strategies implemented in Zambia for agricultural surveillance systems, where lightweight convolutional neural networks have been successfully trained and deployed on mobile devices for real-time monitoring [14].

A qualitative testing phase was conducted to evaluate the performance, usability, and responsiveness of each module. Feedback from simulated end-users (health professionals and data managers) guided interface adjustments and backend optimizations to ensure the system was suitable for deployment in Zambia's decentralized healthcare infrastructure.

A. Analysis and Design

The design architecture of the GIS-based disease outbreak monitoring application is structured around three primary functional layers: data ingestion, geospatial visualization, and AI-powered qualitative analysis. Each layer is developed to support modular interaction while maintaining system responsiveness, scalability, and ease of use for non-technical public health personnel.

A. Data Ingestion Module

The system features a secure, form-based data ingestion interface allowing for both manual entry and bulk uploading of CSV files. The input schema includes parameters such as patient ID (anonymized), date of diagnosis, location coordinates, age group, disease type, and severity. Real-time input validation is performed client-side using Flutter's form validation libraries to ensure data consistency before storage in Firestore.

The ingestion module is designed to operate under low-bandwidth conditions and is optimized for offline-first behavior using Firebase's local caching capabilities. This functionality is aligned with real-world deployments in rural environments, where intermittent connectivity can limit continuous cloud access [15].

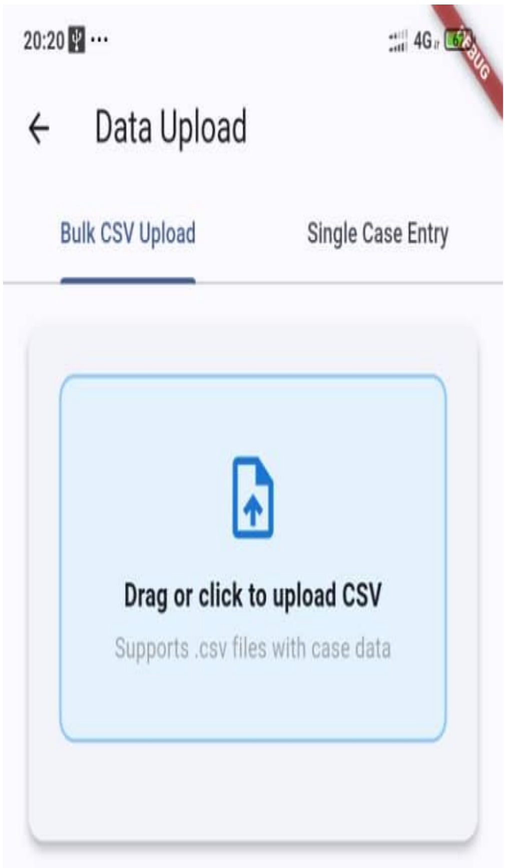

Fig. 1. Bulk CSV Upload Interface for Disease Data Entry.

Fig.1 screen from the mobile application displays the "Data Upload" module, allowing users to upload structured outbreak data in .csv format. The interface offers two input modes: Bulk CSV Upload and Single Case Entry. The upload area is designed with clear prompts for health workers to drag-and-drop or click to import files, streamlining batch data ingestion for field deployments in low-resource settings.

Fig. 2. Preview of Uploaded Disease Case Records from CSV File.

After a bulk upload, the system displays a table preview of the first few entries parsed from the CSV file. Each record includes a unique caseId and the associated disease type, such as Malaria, Cholera, Typhoid, and Influenza. Fig 2. preview allows the user to verify data accuracy before submission, enhancing transparency and preventing errors in outbreak case ingestion.

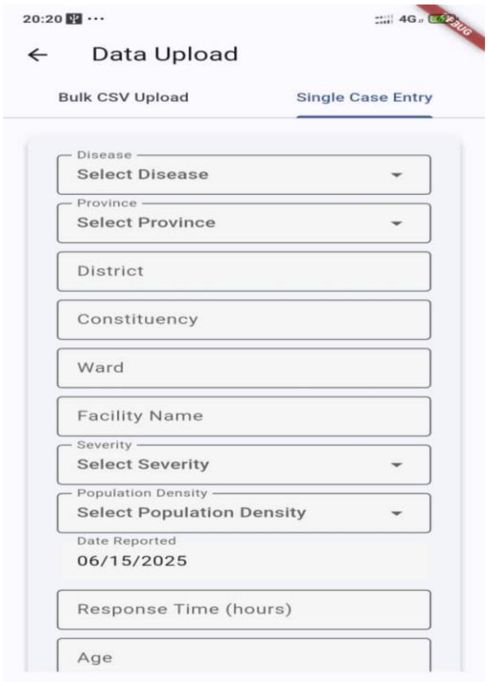

Fig. 3. Single Case Entry Interface for Manual Disease Reporting.

Fig. 3. interface enables health professionals to enter outbreak case data manually when CSV upload is not feasible. The form includes fields for disease type, location hierarchy (province, district, ward), facility name, severity level, population density, and demographic indicators such as age and response time. Dropdown menus ensure standardized data input, supporting accurate real-time reporting in the field.

B. Geospatial Visualization Layer

A central component of the platform is the interactive map interface, built using Google Maps SDK for Flutter. Disease cases are plotted dynamically using location coordinates, with clustering logic implemented to minimize visual clutter and enhance spatial pattern interpretation.

Clusters are rendered based on case density within proximity thresholds, and each cluster displays metadata such as dominant disease type and average case severity. Visual enhancements like ringed severity indicators and zoom-level dependent granularity are incorporated to facilitate multiscale analysis by public health officers.

The design of this layer draws from global best practices used in pandemic visualization dashboards, such as those developed during the

COVID-19 outbreak [16]. These systems proved the importance of responsive spatial interfaces that allow users to detect emergent clusters and explore regional case variation.

Fig. 4. Interactive Outbreak Map Displaying Regional Disease Clusters.

Fig.4 geospatial interface displays real-time outbreak clusters across different provinces in Zambia, including Lusaka, Central, Copperbelt, and Southern Provinces. Circle markers indicate the number of reported cases per region, with cluster severity color-coded (e.g., green for low, red for high). Users can zoom in to view local-level detail or tap clusters to access specific case information, supporting spatial analysis and hotspot identification.

Fig. 5. Interactive Cluster Popup Showing Typhoid Case Summary.

Fig. 5 zoomed-in view of the outbreak map reveals a dynamic popup triggered by tapping a disease cluster. The popup displays metadata including disease type (Typhoid), severity level (Low), total case count, and first/last reporting dates. This feature enhances user interactivity and provides rapid situational awareness, enabling health professionals to assess local outbreak status at a glance.

C. AI-Powered Analysis Engine

Structured disease data is transmitted securely to the DeepSeek & Gemini API, which returns a narrative analysis including outbreak trends, potential correlations (e.g., with weather or location), and suggested health interventions. This analysis is parsed and displayed in the user dashboard using Flutter's widget tree for real-time user interface updates.

While this current version depends on an external AI API, the long-term design objective is to replace this component with a locally trained AI model, enabling improved interpretability, reduced latency, and offline functionality. This mirrors recent Zambian AI deployments in agriculture, where locally trained CNN models were effectively embedded in edge devices [17].

Together, these components form a cohesive and extensible system designed not only to visualize disease spread but to support predictive health analytics and proactive intervention planning in Zambia's public health infrastructure.

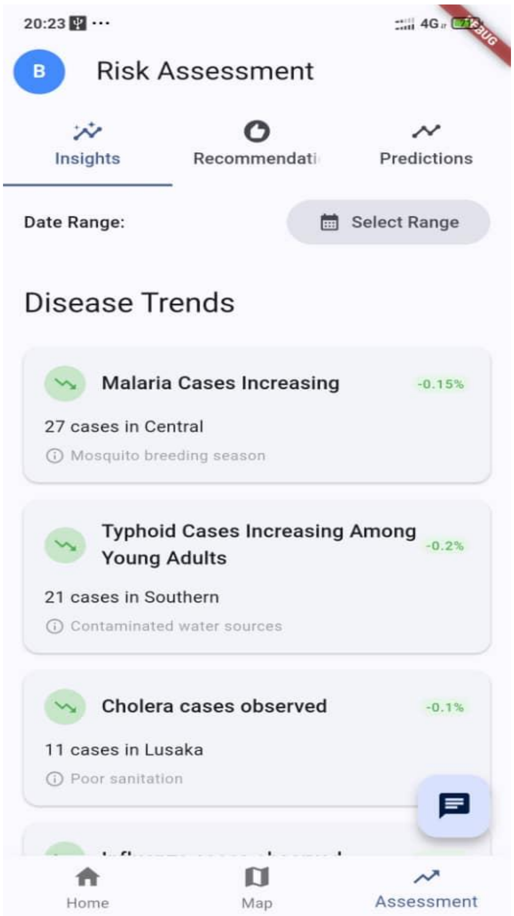

Fig. 6. Risk Assessment Dashboard Displaying AI-Derived Disease Trends.

Fig. 6 interface provides real-time trend insights on diseases such as malaria, typhoid, and cholera. Each entry summarizes the change rate in reported cases, geographic concentration, and associated environmental risk factors (e.g., mosquito breeding, contaminated water, sanitation). This module uses AI analytics to surface early warning indicators and prioritize public health responses by region and disease type.

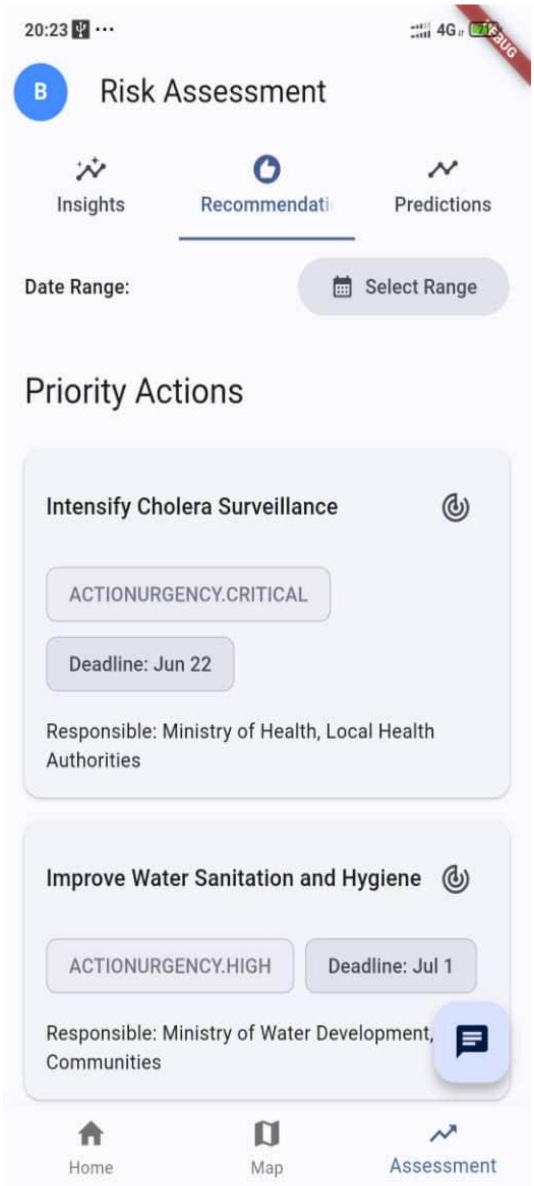

Fig. 7. Priority Action Panel Suggesting AI-Driven Public Health Interventions.

Fig. 7 interface presents recommended interventions based on risk assessment insights, prioritized by urgency and deadline. For example, the system suggests intensifying cholera surveillance and improving sanitation, with responsible agencies clearly indicated. Action urgency tags (e.g., CRITICAL, HIGH) help health authorities allocate resources and coordinate response efforts effectively.

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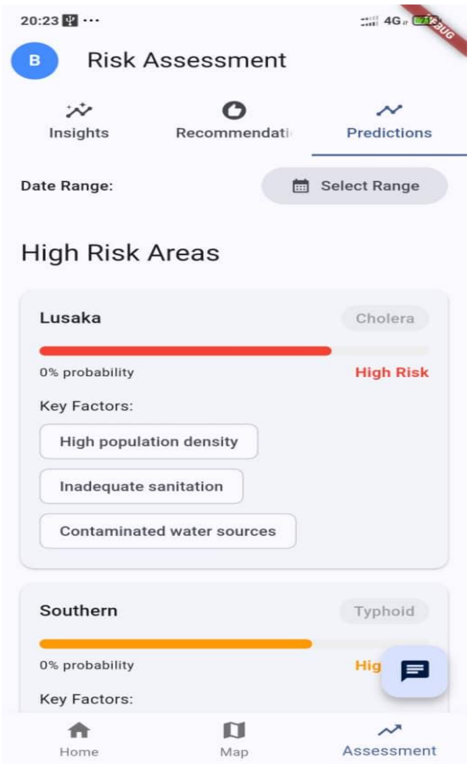

Fig. 8. Predictive Risk Assessment of Cholera and Typhoid by Region.

In Fig. 8, the system uses AI to forecast regions with high outbreak risk based on environmental and demographic factors. Lusaka is flagged as a high-risk zone for cholera due to high population density, poor sanitation, and contaminated water sources. Similarly, the Southern region is predicted at high risk for typhoid. Color-coded bars and contextual tags allow for intuitive interpretation by decision-makers.

RESULTS

The prototype of the GIS-based disease outbreak application was successfully developed and tested in a controlled environment simulating real-world conditions in Zambia's public health context. The system demonstrates integrated functionality across its three core modules: interactive mapping, dashboard analytics, and AI-powered insights.

A. Interactive Mapping

The geospatial interface accurately maps disease case data onto an interactive Google Map layer. Each case is plotted based on user-input coordinates, with real-time rendering of clustered outbreak zones. Clustering adjusts dynamically based on zoom level, ensuring clarity whether viewing national-scale trends or localized hotspots. Users can tap on clusters to retrieve case metadata, including dominant disease, number of cases, and location-specific severity statistics.

This functionality parallels global systems used during the COVID-19 pandemic to visualize outbreak trajectories [18], confirming the viability of such tools in enhancing situational awareness among public health officials.

B. Dashboard Analytics

The dashboard module aggregates disease data into meaningful summaries using bar charts, pie charts, and time-series plots. Key indicators include:

- Total case counts by disease type
- Demographic breakdowns by age and gender
- Weekly and monthly trend curves
- Spatial distribution heatmaps

The dashboard was designed for quick interpretation, even by non-technical users, and is responsive across both desktop and mobile platforms. The visual style adheres to data visualization principles established in previous mobile GIS implementations for disease management in East Africa [19].

C. AI-Powered Insights

The AI module successfully processed structured data submitted through the dashboard and returned actionable insights. Sample outputs included:

- Identification of emerging hotspots based on multi-case clusters
- Hypothesized correlations between rainfall data and outbreak spikes
- Recommendations for increased health messaging in densely affected areas

These outputs are displayed in a structured narrative format on the dashboard, enhancing decision-making capabilities for field officers and health planners. This approach reflects successful implementations in digital agriculture and pest monitoring, where localized AI-driven recommendations improved both timeliness and relevance of interventions [20].

Collectively, the system offers a scalable and adaptable architecture that not only supports spatial awareness but also embeds intelligence directly into field-level workflows, paving the way for data-informed disease response strategies in Zambia.

CRITICAL EVALUATION

The development and testing of the GIS-based outbreak monitoring system yielded several important insights into the technical and operational challenges of deploying intelligent health surveillance platforms in low-resource environments.

The use of modern mobile development frameworks (Flutter and Firebase) enabled rapid prototyping and scalability, while the integration of AI-driven analytics through the DeepSeek & Gemini API added substantial decision support value. The application demonstrated strong functionality in offline-tolerant data collection, multi-scale geospatial visualization, and real-time feedback, all of which are essential features for health workers operating in decentralized or rural settings.

Furthermore, the clustering logic and severity mapping techniques incorporated into the visualization layer enabled meaningful detection of outbreak patterns across different geographic scales. This aligns with geospatial visualization standards in digital epidemiology platforms used in COVID-19 dashboards globally [21].

CONCLUSION

This research successfully developed and evaluated a GIS-based mobile application designed to enhance disease outbreak surveillance in Zambia through the integration of geospatial mapping and AI-powered analytics. By leveraging open-source technologies such as Flutter and Firebase, alongside a third-party AI service, the prototype demonstrated core capabilities including real-time case mapping, dynamic clustering, and automated insight generation.

The application's functionality aligns with global digital health standards, yet it is tailored specifically to the infrastructural and epidemiological realities of Zambia. Its mobile-first design and offline tolerance make it particularly suitable for deployment in rural and underserved areas where conventional health information systems often fail to provide timely data.

Unlike traditional systems like DHIS2, which emphasize historical reporting and aggregated analysis, this platform introduces spatial intelligence and predictive modeling at the point of data entry. This supports a shift from reactive to proactive public health interventions, allowing stakeholders to identify outbreak patterns, anticipate escalation, and allocate resources accordingly.

The qualitative evaluation of the system, informed by simulated user testing, confirms its usability and relevance. However, limitations such as external AI dependency and lack of locally trained models underscore the need for continued development[22],[23]. Ultimately, the system offers a scalable framework for integrating AI and GIS in public health, a model that can be extended to other low-income countries with similar healthcare and infrastructural challenges. Prior successes in Zambia's digital agriculture domain provide a strong foundation for this transition, where mobile-based AI tools have already demonstrated tangible impact in early warning and resource coordination efforts [24].

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