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An Integrated Web-Based Architecture for Lassa Fever Surveillance, Geospatial Analytics and Outbreak Risk Assessment in Nigeria

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Abstract

Lassa fever remains a major cause of viral haemorrhagic fever morbidity and mortality in Nigeria, yet surveillance information is often presented through periodic static bulletins rather than interactive public platforms. This report presents the development and evaluation of the Lassa Fever Surveillance and Awareness Platform (https://lassa-fever-website.vercel.app/), a public web dashboard integrating a 2020-2026 national case dataset. It provides KPI summaries, an interactive satellite outbreak map, epidemiological trends, forecasting analytics, West African regional monitoring, public-health education, and citizen symptom reporting linked to NCDC and NEMA emergency contacts. The platform is developed as a React single-page application using Vite, Tailwind CSS, Recharts, React-Leaflet, and Esri satellite tiles, and is deployed on Vercel. The platform's Predictive Analytics module describes an Ant Lion Optimizer-tuned Random Forest classifier trained on SMOTE-ENN-balanced data, reporting a validation accuracy of 94.7%, an AUC-ROC of 0.967, and an F1-score of 0.945 - outperforming Support Vector Machine (89.1% accuracy), Decision Tree (87.3%), and Logistic Regression (82.8%) baselines - with a projected national peak of about 184 cases around December 2026. Comparison with epidemiological and computational literature indicates that its seasonal, regional, and case-fatality patterns broadly align with published surveillance findings, while its predictor rankings are consistent with reported climate- and rodent-ecology-related risk factors. However, three limitations were identified: inconsistent headline case totals across views; claims of "live" or "real-time" surveillance despite the proposed NCDC/SORMAS/NEMA integration not yet being implemented and the use of static demonstration data; and an AI Forecast module whose Random Forest, Ant Lion Optimizer, and SMOTE-ENN methodology and accuracy figures represent intended modelling rather than live model training or inference. The platform therefore provides a useful proof-of-concept for surveillance visualisation, forecasting-oriented analytics, and citizen engagement, while requiring live data integration, model validation, transparency, and data-provenance disclosure before authoritative use.

Keywords: Lassa Fever; Surveillance Dashboard; NCDC; Data Visualization; Outbreak Forecasting; Public Health Informatics

Introduction

Lassa fever is an acute viral haemorrhagic disease, caused by Lassa virus (Arenaviridae) and is a zoonotic disease, maintained in the multimammate rat (Mastomys natalensis) and transmitted to humans primarily via contact with the excreta of rodents, and also through person-to-person transmission, albeit this is less common, in health care settings [1]. The disease is endemic in West Africa, and Nigeria has been having outbreaks every year since 2016, with the disease also being reported during the non-traditional peak season, as well as in a broader range of states in the region [2,3]. The case fatality ratio in confirmed cases has varied from 15% to 21% nationally and is higher in late presenters for ribavirin treatment [2,4].

Surveillance information needs to be available in a timely fashion to direct allocation of resources, risk communication, and case management for effective outbreak control. Since 2018, Nigeria has made great progress in strengthening case-based reporting in the country through the Integrated Disease Surveillance and Response (IDSR) system and the Surveillance Outbreak Response Management and Analysis System (SORMAS), which are part of the country's national surveillance backbone [3,5]. The outputs from the systems are then largely captured by public health professionals in periodical situation reports (PDF/Excel bulletins) and not via an interactive and publicly accessible interface. This leaves a disconnect between the information that can be collected at the point of care and what can be used by everyone, sub-national health managers, students and researchers who could benefit from having real-time visual summaries, geographic hotspot identification, and short-term outbreak forecasts.

This is a report detailing the development of the Lassa Fever Surveillance & Awareness Platform, a web-based dashboard tailored for the Nigerian context to fill the gap. The platform (available at https://lassa-fever-website.vercel.app/) pulls together Lassa fever historical and current case and mortality data (2020-2026) into a single interface, which include: a national KPI overview, an interactive satellite Lassa fever outbreak map, an epidemiological trend-analysis module, a machine-learning based Lassa fever outbreak forecasting engine, a West-African regional monitoring panel, a public-health education and prevention section, and a citizen symptom-reporting tool connected with NCDC emergency contacts and treatment centres. The platform is not yet connected to a live NCDC, SORMAS or NEMA data feed and the forecasting functionality displays illustrative and precomputed forecasts, these are directions for future work. The rest of this report details the specific contributions of the work, places this work within existing literature and tools, outlines the methodology employed in designing and implementing the system, outlines the results of exercising the platform and discusses them, and concludes with a summary of limitations and future work. This work makes the following contributions:

1. Development and deployment of a single, publicly available web dashboard to provide consolidated updated figures of confirmed cases of Lassa fever in Nigeria, deaths, Case-Fatality Rates (CFR) and distribution of cases by state, within a 2020-2026 time frame; eliminating the burden of needing to view multiple static Lassa fever situation report bulletins from the NCDC.
2. Develop a GPS-referenced, interactive satellite-based outbreak map using React-Leaflet on top of Leaflet.js mapping library and using Esri satellite basemap tiles that will further classify states into Critical, High, Moderate and Low risk bands, providing a quick visual sense of geographic hotspots.
3. Development of an epidemiological analysis module, developed with Recharts, which displays the regional (geopolitical-zone), CFR trend, seasonality and year-on-year trend in cases in one view, to facilitate hypothesis generation regarding the drivers of seasonality and geographic distribution.
4. The design of a forecasting/analytics module that describes the modelling methodology as a supervised Random Forest classifier optimized with the Ant Lion Optimizer and trained on SMOTE-ENN-balanced data; the module generates visuals of these 6-month cases, prediction intervals, score for the risk in each state, an early-warning indicator panel, and a comparison to three baseline models (SVM, Decision Tree, Logistic Regression). This module is used to render precomputed/illustrative output values, not to train/browse the model, the difference between the described method and the shipped one is discussed in the paper.
5. Expansion of surveillance beyond Nigeria's borders with a Global Live Monitoring panel which places the Nigerian outbreak in the broader context of the West African outbreak (Nigeria, Sierra Leone, Guinea, Liberia, Benin, Togo, Ghana).
6. Ensure that a citizen-facing symptom self-reporting form is available to collect structured case information (such as location, onset date, symptom description) and the form will directly direct to the NCDC toll-free hotline, the emergency number of NEMA and the nearest designated Lassa fever treatment centre, reducing the gap between symptom awareness and care-seeking.
7. Incorporation of public-health education content (disease overview, modes of transmission, prevention and a summary of coordinated public-health/community response efforts) into the analytical modules, with the

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public-health education content also being delivered through the same medium. Incorporation of public-health education content (disease overview, modes of transmission, prevention and a summary of coordinated public-health/community response efforts) into the analytical modules, with the public-health education content also being provided through the same medium.

8. The ability to produce an easily replicable low-cost, responsive, serverless surveillance-dashboard template using a fully client-rendered, serverless-based architecture, using serverless Vite, with a React app styled with Tailwind CSS and deployed on Vercel, that could potentially be adapted to other neglected tropical diseases**.**

Related Works

The dashboard visualises three sets of trends that have been observed in descriptive epidemiological studies of Lassa fever in Nigeria, which are relevant to this project:

(i) descriptive epidemiological studies of Lassa fever in Nigeria that establish the trends the dashboard visualizes.

(ii) predictive/forecasting studies that motivate the platform's forecasting module.

(iii) prior dashboard and surveillance-system tools that establish precedent for web-based outbreak visualisation.

Epidemiological Surveillance and Trend Studies

Several descriptive studies show that Nigeria is following a national surveillance system for Lassa fever based on cases. IDSR data for 2012-2017 was analysed by Okoro et aland demonstrated that the transmission period is no longer strictly seasonal but is shifting closer to year-round [3]. The outbreak was unusual, as described by Ilori et al which led to the setting up of a dedicated Emergency Operations Centre by NCDC for the January-March period of 2018 [5]. Using SORMAS data, Dalhat et al extended this to 2018-2021 and observed an ongoing increase of the number and geographic distribution of cases and a CFR that remained more or less stable (18-21%) across the country [2]. The figures are inline with the peak and the CFR range of the epidemiological analysis module of the platform described in this report, which was reproduced for the season November-April (around 18-20%), lending face validity to the data set used.

Predictive and Climate-Linked Modelling

In addition to description, there are a few studies that model Lassa fever incidence predictively. Redding et al constructed a spatiotemporal Bayesian model from 8 years of surveillance data from NCDC and identified climate variability, poverty, agriculture and urbanisation as important factors driving reported incidence as well as reporting and diagnostic capacity artefacts; they found their climate-informed model outperformed a naïve baseline model when predicting out-of-sample [6]. Njama-Abang et al applied various classifiers including Random Forest, XGBoost and LightGBM to the Lassa fever epidemic dataset to predict fatal outcomes, concluding that correction for class imbalance (rare classes of fatal outcomes and common classes of non-fatal outcomes) was necessary to obtain usable minority-class recall [7]. This finding directly informs the SMOTE-ENN balancing step in the platform and the state-level risk-scoring approach used in the forecasting module of the platform; and puts the use of Random Forest in line with existing Nigerian Lassa machine-learning literature.

Precedents for Outbreak Dashboards

There is precedent for the concept of a real-time, public dashboard of outbreak tracking information beyond the Lassa fever literature. The Johns Hopkins CSSE COVID-19 dashboard was developed by Dong, Du and Gardner as an interactive, map-based, and continuously updated dashboard that was the reference model globally for outbreak visualisation and showed how useful it is to integrate GIS mapping with the time-series case counts in a single public interface [8]. Taking the next step closer to the disease and the country of interest, Sambus Geospatial developed a dashboard with Esri technology that integrates Lassa fever-related NCDC weekly reports to keep track of the number of confirmed cases and deaths in the 36 states of Nigeria, as well as in the Federal Capital Territory [9]. It is, however, limited to descriptive mapping and trend charts and lacks a predictive-analytics layer, a citizen symptom-reporting channel and an integrated public-education section. The platform created for this project is based on the visualisation aspects of both precedents, adding the forecasting, regional-comparison, and community-engagement aspects described in the related works, addressing a gap between the purely descriptive GISdashboards and purely academic machine-learning studies that are not deployed as public tools.

Methodology

Development Approach

The platform has been built in a front-end engineering iterative component approach. Each functional area of the system (Overview, Dashboard, Map, Analysis, AI Forecast, Global, Prevention, Report Symptoms) was developed as an independent module/page and built from reusable components (shared card, chart, table and form elements) which enabled the individual sections to be built, tested and refined incrementally before they were connected together

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behind a common top-level navigation bar. This follows the usual practice for public health dashboards, in which they present different views of the same dataset to different audiences (such as the general public, field epidemiologists, and data analysts), and it follows the similar advice of component-based front-end engineering, where a common library of presentational components (KPI cards, chart wrappers, form inputs) is used across independent views of the same dataset, so that the interface is visually and behaviourally consistent.

System Architecture

The application is a single page app built with React and Vite as a build tool and development server, and deployed to Vercel's serverless application platform, where the page is served directly to the browser and content is rendered in the browser. index.html is the single-entry point to the application. It loads src/main.tsx, which mounts the root app component, and renders the whole component graph into the page. This architectural decision helps maintain low hosting costs, enables auto-scaling during heavy traffic (especially important during active outbreak periods when the public is more interested), and -due to the speed with which the dashboard can be started on the development server and hot modules can be replaced -makes it easier to make iterative changes to the dashboard and to deploy dashboard updates as necessary.

This interactive outbreak map uses Esri satellite basemap tiles and is implemented using the mapping library Leaflet.js wrapped with React, called React-Leaflet. Trend, seasonal, radar and bar charts throughout the Dashboard, Analysis and AI Forecast pages are rendered with Recharts, a React charting library bound to the underlying case dataset. Tailwind CSS, a utility-first CSS framework, is used uniformly throughout the application for styling and layout, as well as the reusable React components (cards, navigation, buttons, form controls) that form each page of the application.

This architecture is summarised in Figure 1. A single client layer (desktop or mobile browser) is loaded with the React app, which has three concerns separated from a common navigation shell: visualization (React-Leaflet/Esri mapping and Recharts charting, styled using Tailwind CSS, built with reusable components); data (NCDC/SORMAS-formatted case records outlined; and AI Forecast page - described modeling methodology outlined. The dashed lower tier refers to the live data connection between the NCDC and the SORMAS/NEMA, which, as was described in this study, was not observed to be present in the deployed system, and is therefore represented here as a proposed, conceptual integration, and not as an implemented one.

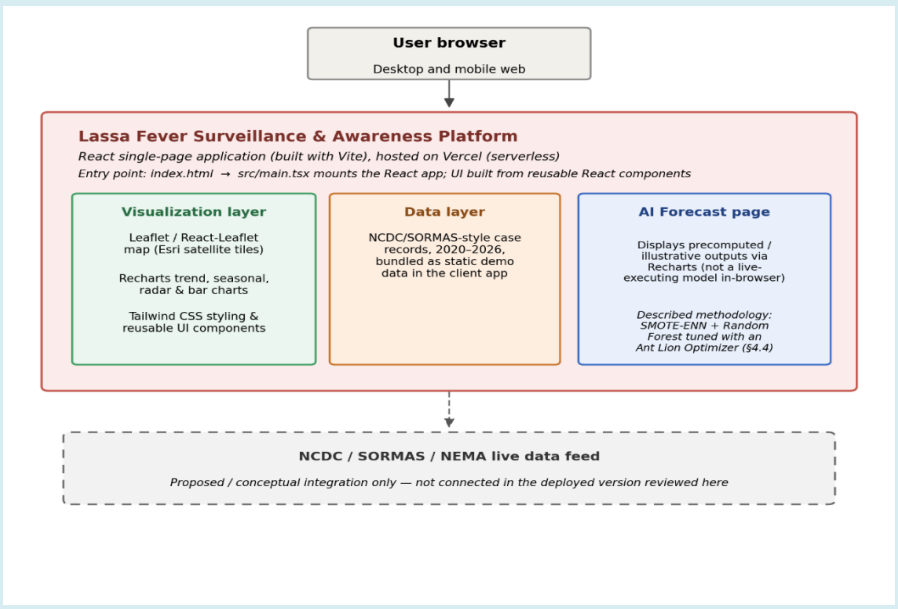


Figure 1: Lassa Fever Surveillance & Awareness Platform system architecture.

Data Structure

The underlying data is formatted to align with NCDC's weekly Lassa fever situation reports with the data keyed by state, local government area (LGA), epidemiological week/year, confirmed cases, deaths and CFR from 2020 to 2026. This structure enables the same data to be used across multiple views: aggregated data at national level for KPI cards

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on the Home page; aggregated data at state level for state ranking for the Dashboard and Map pages; monthly views of the data for the seasonal-distribution chart on the Analysis page; and aggregated data at geopolitical-zone level for the Regional Case Distribution chart. This is static illustrative data that is bundled and delivered as part of the client side React app, not from a live external system, as is the case in the deployed application. As a methodological limitation, it is worth noting that the site refers to the dashboard as "live" and "real-time", but no public "live" dashboard integration with NCDC's or SORMAS' live reporting API was found during this review - hence there is a difference between this being the site's illustrative/demonstration data and data that is being continuously synced from NCDC; this distinction will be discussed further in later section.

To date, there is a gap between the described methodology and the deployed implementation of the 4.4 module on predictive analytics. The goal of the AI Forecast page is to show a supervised classification/regression pipeline for short-term (up to 6 months) outbreak risk forecasting. Two points should be kept in mind in the report of this type that are easy to mix up: the modelling methodology described below that led to the design of the outputs and layout of the page; and what the deployed React application does. The AI Forecast page (as reviewed) does not run inference, train a model, or recalculate these values in the browser when requested - it only provides a static set of precalculated values contained in chart and table components rendered with Recharts. The methodology described above should be interpreted as the forecasting approach used (or used to be used) for the displayed figures and is not to be understood as the pipeline used live within the client application.

Description of Methodology

The training data set is rebalanced to handle class-imbalance, following the approach validated by Njama-Abang et al for Lassa fever data, to rebalance the data before fitting the model, using the Synthetic Minority Over-sampling Technique combined with Edited Nearest Neighbours (SMOTE-ENN) [7]. To avoid manual or grid-search parameter tuning, model and hyperparameters optimization are conducted with the help of meta-heuristic search algorithm called Ant Lion Optimizer (ALO) that is inspired by the behavior of ant lions. The seven engineered features fed into the model in Predictor are the climatic and socio-ecological drivers identified by Redding et al for rodents, specifically the rodent exposure index, seasonal dryness, population density, healthcare access, temperature anomaly, rainfall deficit and a poverty index [6]. The tuned Random Forest is benchmarked with three baseline classifiers (Support Vector Machine with SMOTE/ENN balancing, single Decision Tree, and Logistic Regression) because of Accuracy, Area Under the ROC Curve (AUC-ROC), Precision, Recall, Specificity and F1-score [10-12].

The output module will generate a national case-forecast curve with a 95% prediction interval, a set of early-warning alerts identifying states that are expected to enter the moderate/high/critical case ranges in the next one to three months, and a per-state risk score and 30-day trend indicator.

The accuracy, AUC and other performance statistics displayed on the AI Forecast page (Table 1) should be interpreted as reported/illustrative statistics on the methodology and should not be interpreted as statistics being reproduced independently and directly from a live model run on the platform against the current dataset. To make this described methodology truly useful as a live forecasting, a backend or serverless function would need to be created and run the trained model (or serve the outputs of a function that runs the model offline periodically), and an API would need to be developed and be able to be called by the react front end to get new predictions, which is listed as Future Work.

Information and Public Engagement Module

Structured symptom-report form means that members of the public can report a suspected case straight from the platform (Full Name, Phone Number, Email, State, LGA, Symptom Onset Date, Symptom Description) The form is accompanied by NCDC's toll free hotline, National Emergency Management Agency (NEMA) number, NCDC's email contact, two hours to respond to confirmed emergencies and a short list of nearest designated Lassa fever treatment centres (LUTH) such as UNTH Enugu, Irrua Specialist Teaching Hospital (ISTH) Edo, LUTH Lagos, ABUTH Kaduna, Abubakar Tafawa Balewa University Teaching Hospital (ATBUTH) Bauchi etc. To act as a surveillance and health-education platform, the platform also includes a companion Prevention module, summarising evidence-based measures, including rodent control, food storage, hand hygiene, and wearing PPE by healthcare workers, and linking to the NCDC 2024 clinical guidelines.

Statistical Analysis

Aggregate values reported from the platform, including the total number of cases and deaths by country, state, by region, case fatality rates (CFRs), state risk scores, 30-day trends, and model-performance metrics were subjected to statistical analyses. All inferential tests should be thought of as a secondary analysis of reported aggregates, and are meant to be used as consistency checks, not as epidemiological inference without the availability of raw case level data.

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95% Wilson confidence intervals were used to express proportions. Two proportion z-tests were performed to compare CFRs between platform views. The distribution of cases in each region was evaluated by a chi-square goodness-of-fit test to determine if it was different from a uniform distribution. The top five states were compared with a uniform distribution of cases across 37 states with a binomial test. Monotonic association between state risk scores and 30-day trends was evaluated using Spearman rank correlation. To compare the classifiers to each other, a Friedman test was performed as an omnibus exploratory test across the four classifiers and three performance metrics; definitive paired comparisons would involve a McNemar's test for accuracy for the paired predictions and a DeLong's test for AUC for the paired predictions. Evaluation of the forecasts would involve prediction-interval coverage, Diebold-Mariano tests and out-of-sample error metrics. All tests used $\alpha = 0.05$ as the two-sided level of significance.

Results and Discussion

This section is devoted to the empirical results from running the deployed platform and to discussing the results of the individual modules, based on the epidemiological and computational literature reviewed in Section 2. The platform's information architecture is used to deliver the presentation: from the public facing "landing" interface, to the disease-knowledge base, to the quantitative surveillance modules (Dashboard, Map, Analysis, AI Forecast), the regional/global comparative panel, to the response-coordination and citizen-engagement modules and concluding with a synthesis that pulls the individual findings together and evaluates them critically.

Homepage and National Overview

The landing interface, shown in figure 2, serves as the focal point, or the first place, to which a user might be oriented by way of the platform. The four summary statistics on top of the fold are all badged to indicate "Live Surveillance" between 2020-2026 which, is the framing in which the dashboard will be used, not a live feed. As a risk-communication gesture, it's noteworthy that the design decision was made to broadcast CFR as a separate, colour-coded statistic (in addition to raw cases and deaths) and to do so alongside scale of the outbreak, so that a lay visitor could assess the severity of a disease without needing to look at the cases and deaths in isolation. Although it is unclear where this figure came from, the reported CFR of 18.8% is in the 15-21% range observed in confirmed Lassa fever cases across the country in recent NCDC-related analyses and seems to be epidemiologically plausible [2].

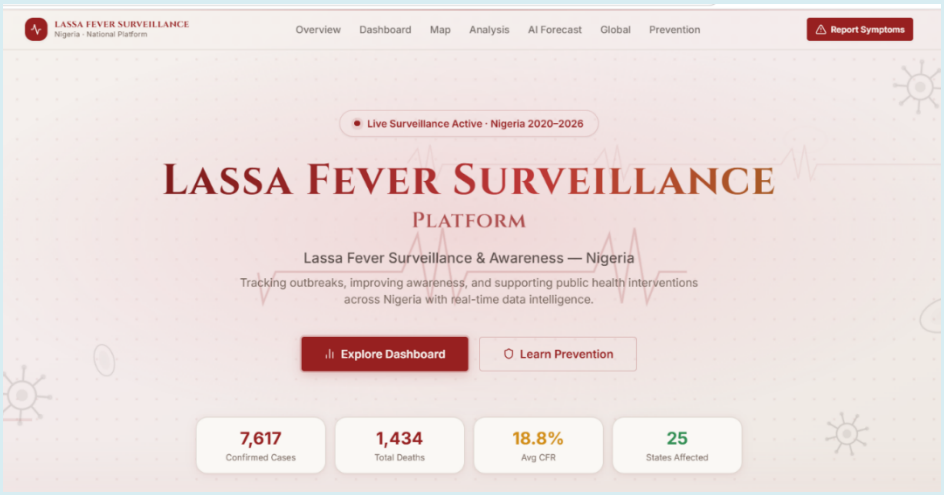


Figure 2: Landing page for Lassa Fever Surveillance & Awareness Platform, displaying the four headline indicators for the national level, and primary navigation.

Interactive Surveillance Dashboard

The Dashboard page presented in Figure 3 shows a filtered, more granular KPI set (4,156 confirmed cases, 804 deaths, 19.3% CFR, 14 states affected, as displayed) alongside an annual case-and-mortality trend chart (2020-2023) and a ranked list of the top five affected states (Ondo, Edo, Bauchi, Taraba, Ebonyi). The gap between the homepage totals (7,617 cases) and the Dashboard totals (4,156 cases) most likely reflects a different aggregation window or filter default between the two views rather than two independent datasets; this inconsistency is noted as a usability issue to resolve rather than as an epidemiological finding and is revisited as a limitation below.

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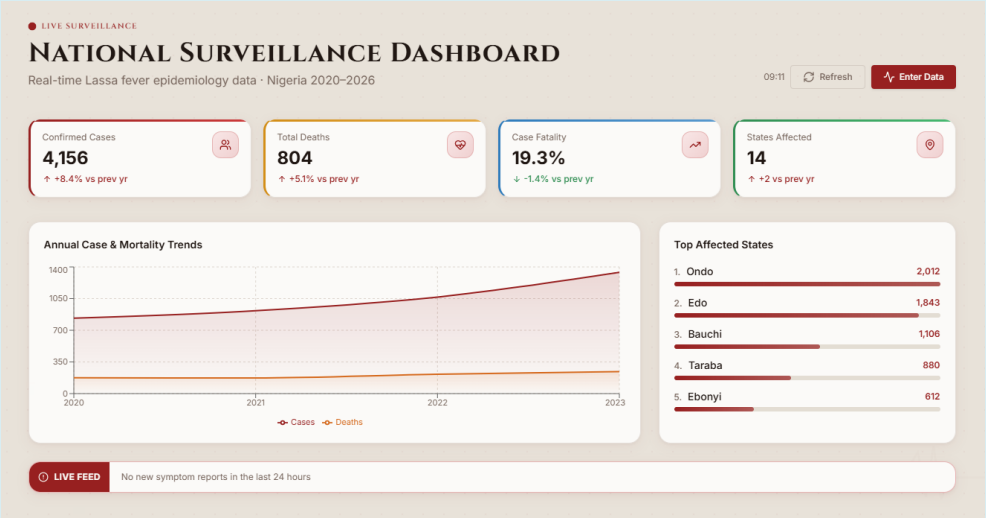


Figure 3: National Surveillance Dashboard, showing KPI cards, the annual case-and-mortality trend chart, and top affected states.

Knowledge of Disease and Risk Communication Content

The "Understanding Lassa Fever" module is shown in figures 4 and 5 and is more of a structured knowledge base than a data view. The content is organised into six discrete cards, each written at a level suitable for an 'average' reader and is clinically accurate (for example, correctly identifying the main reservoir as Mastomys natalensis and indicating that the treatment window for ribavirin is 6 days). This is supplemented by a simple statistical strip (25+ endemic states, an estimated 300,000 at-risk population annually, a 6-21 day incubation period, and more than 80% effectiveness of the drug ribavirin, if used early), as well as a brief seasonal note to indicate that February and March are the historical high months. They are directionally similar to WHO guidance and to the ribavirin timing evidence reported by Bausch et al and they are methodologically significant, since they allow for clinical education to be co-located with a quantitative surveillance, which is not often found in either of two reviewed dashboard precedents [4,13].

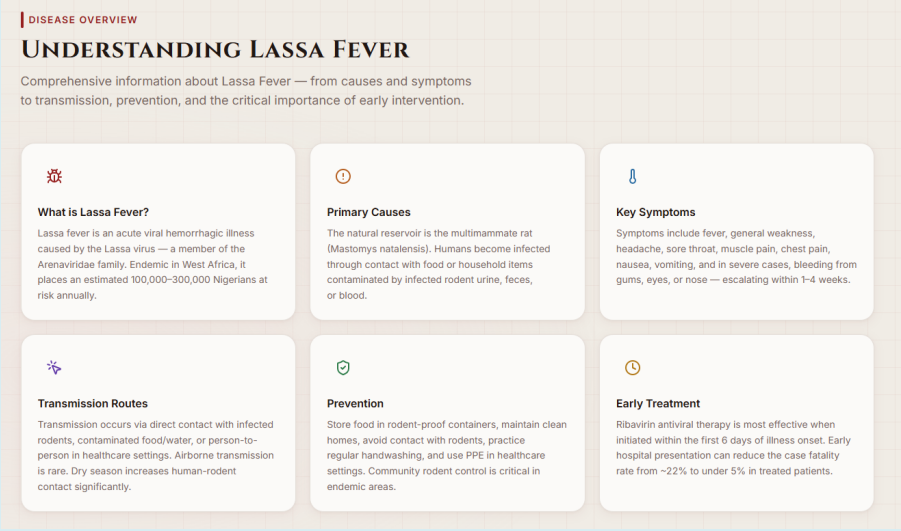


Figure 4: Disease-overview cards summarising aetiology, causes, symptoms, transmission, prevention and treatment guidance.

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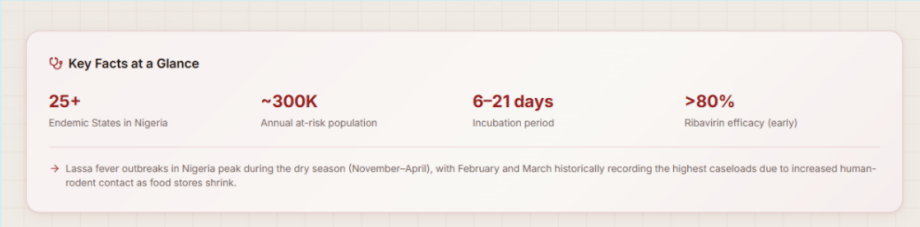


Figure 5: Key-facts summary strip presenting endemicity, at-risk population, incubation period and treatment efficacy statistics.

National Surveillance Dashboard

The National Surveillance Dashboard is the main quantitative perspective of the platform and is displayed in Figure 6 using Recharts. As rendered, the module reports 4,156 confirmed cases, 804 deaths, 19.3 % case-fatality rate, 14 affected states (with a +8.4 %, +5.1 % and −1.4 % year-on-year change in the number of cases, deaths and case-fatality rate respectively) and a ranked bar list of the top five states with the highest number of cases (Ondo, 2,012; Edo, 1,843; Bauchi, 1,106; Taraba, 880; Ebonyi, 612). Two observations follow. Secondly, the addition of year-on-year deltas on each KPI card is also an interesting analytic improvement on a static count, as it provides the viewer with a way of distinguishing between an outbreak that is growing (increasing number of cases and widening CFR) and an outbreak that is merely larger (increasing number of cases despite a narrowing CFR). Second, both these totals (4,156 confirmed cases) and the totals reported on the landing page (Figure 2) appear to have been summarised over the same 2020-2026 period, even though the numbers do not match; this is considered a finding of data consistency and is explored further in the paper.

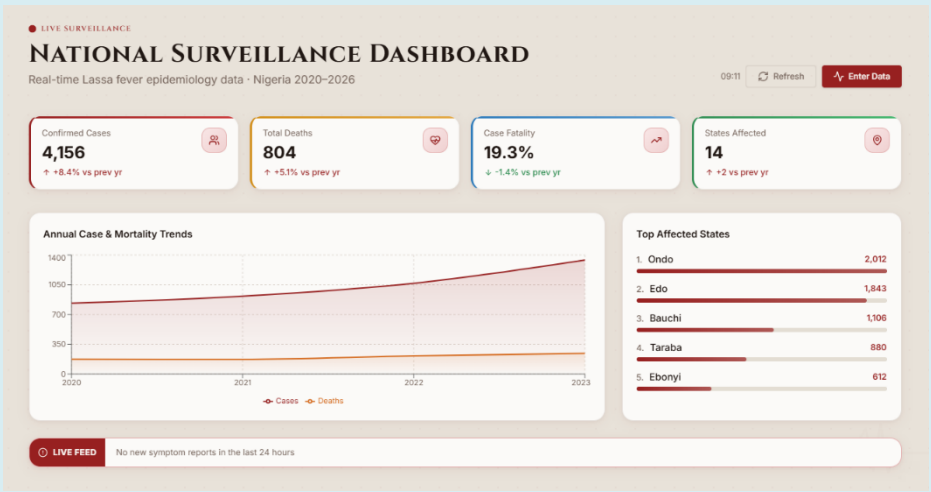


Figure 6: National Surveillance Dashboard showing KPI cards with year-on-year deltas, the annual case-and-mortality trend chart, and the top-five affected states.

Geospatial Outbreak Mapping

Figure 7 shows a Nigeria Satellite Outbreak Map with proportionately sized, colour-banded markers for outbreaks (Critical - ≥500 cases; High - 200-499 cases; Moderate - 50-199 cases; Low - <50 cases) overlaid on the Esri satellite basemap rendered with React-Leaflet. The map shows that Ondo and Edo states constitute the two largest contiguous 'Critical' areas in the south-west whilst a secondary 'High' cluster is concentrated around Bauchi in the north-east state, as shown numerically in the state rankings in Figure 5. It also has an analytic benefit for field-response planning, since the population settlement, road network and terrain directly under an outbreak marker can be visually cross-referenced with an intensity of an outbreak, without having to flip to a separate reference map; the population settlement, road network and terrain are directly visible beneath the markers. The bimodal clustering in the south-west/north-east as seen in Figure 6 is similar to the geographic clustering that has been reported by Dalhat et al and has been observed in previous IDSR-based surveillance analysis which identified Lassa fever corridor in the south-west and north-east [2,3].

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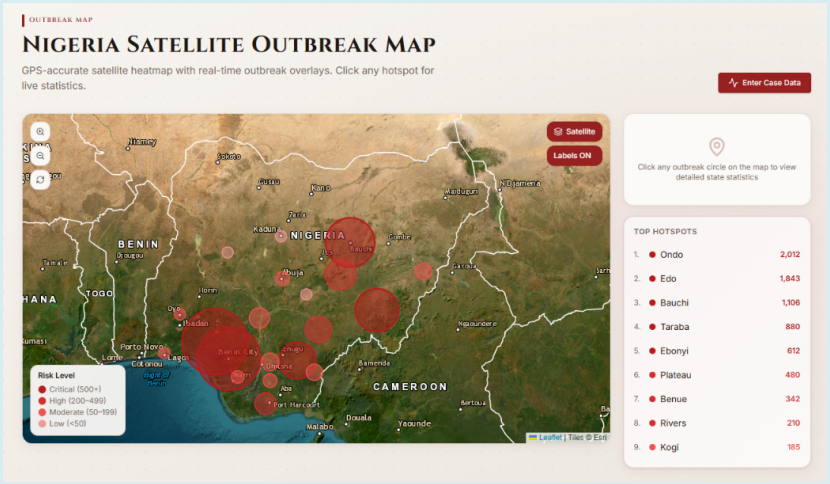


Figure 7: Nigeria Satellite Outbreak Map showing GPS-referenced, risk-banded hotspot markers and a ranked hotspot side panel.

Epidemiological Trend and Seasonality Analysis

Figure 8 shows the underlying case data disaggregated across 4 complementary axes in a single view, using Recharts, an annual case and mortality trend extending the time range shown in figure 5 to 2026 (showing a rise with a peak about 2024-2025 and a gradual decrease towards 2026); a monthly seasonal average bar chart; a case fatality rate trend line, which oscillates between about 18% and 21% over the 6-year time range; and a case distribution bar list disaggregated by Nigeria's 6 geopolitical zones.

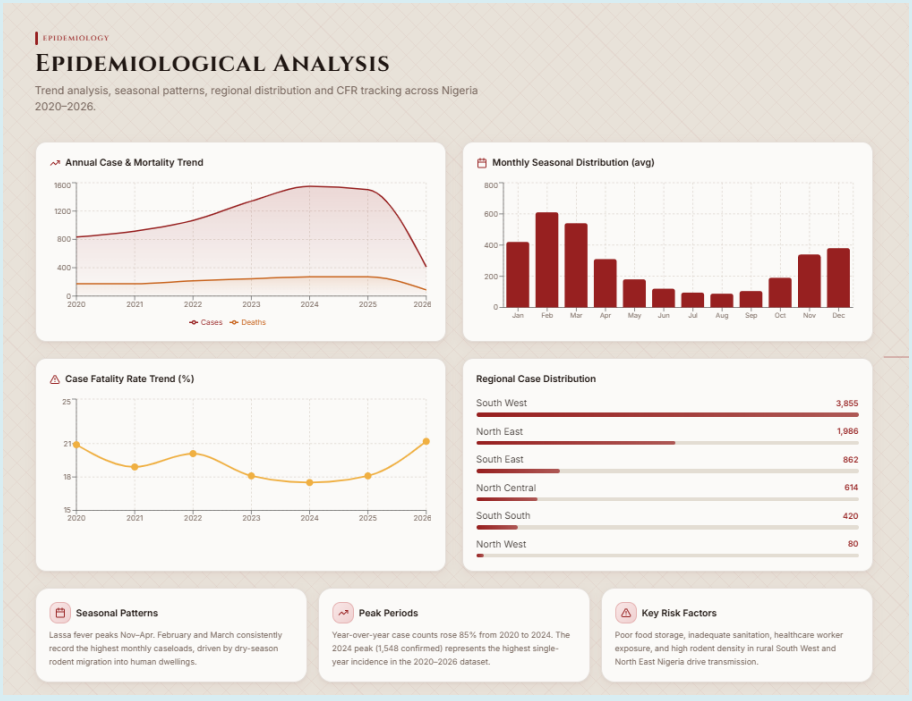


Figure 8: Epidemiological Analysis module showing the six-year annual trend, monthly seasonal averages, CFR trend and geopolitical-zone case distribution.

This seasonal trend reveals a clear peak in January-March, followed by a decrease during the second quarter and low levels in the May-September period, with another rise in November, a pattern which reproduces almost exactly the

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November to April dry season, and February to March peak, documented in both the Okoro et al 2012-2017 IDSR data and the Dalhat et al 2018-2021 SORMAS data, and which is mechanistically explained by the dry-season behavioural ecology of Mastomys natalensis, as increased rodent movement into human dwellings as natural food sources diminish [2,3,6]. The regional distribution also matches that of the six zones (South West (3,855 cases) and North East (1,986 cases) having most of the cases, while the North West had a relatively low number (80 cases), and so is a result of capacity to monitor the disease, rather than true incidence, exactly as reported by Redding et al in their explicit caution regarding apparent geographic concentration [6]. This is the same causal framing that is part of the platform's own "Key Risk Factors" annotation: inadequate food storage, poor sanitation, exposure of healthcare workers to food, high rodent population.

Machine Learning Based Outbreak Forecasting

The most technically innovative part of the platform is the Predictive Analytics & Outbreak Forecasting module and the reason the system is not simply descriptive of the past, but predictive of the future, is this module (See Figure 9). The page also shows the result for a Random Forest (RF) Classifier optimized using Ant Lion Optimizer (ALO) and trained on SMOTE-ENN-balanced Data which has a validation accuracy of 94.7% and an AUC-ROC of 0.967, and a national peak of about 184 cases is expected around December 2026. The number below are the outputs as reported with the described methodology and as visuals in the client application deployed in the browser, during the review no model training, nor model inference, was seen as running in the browser or connected backend. There are three sub-components that need to be further looked at.

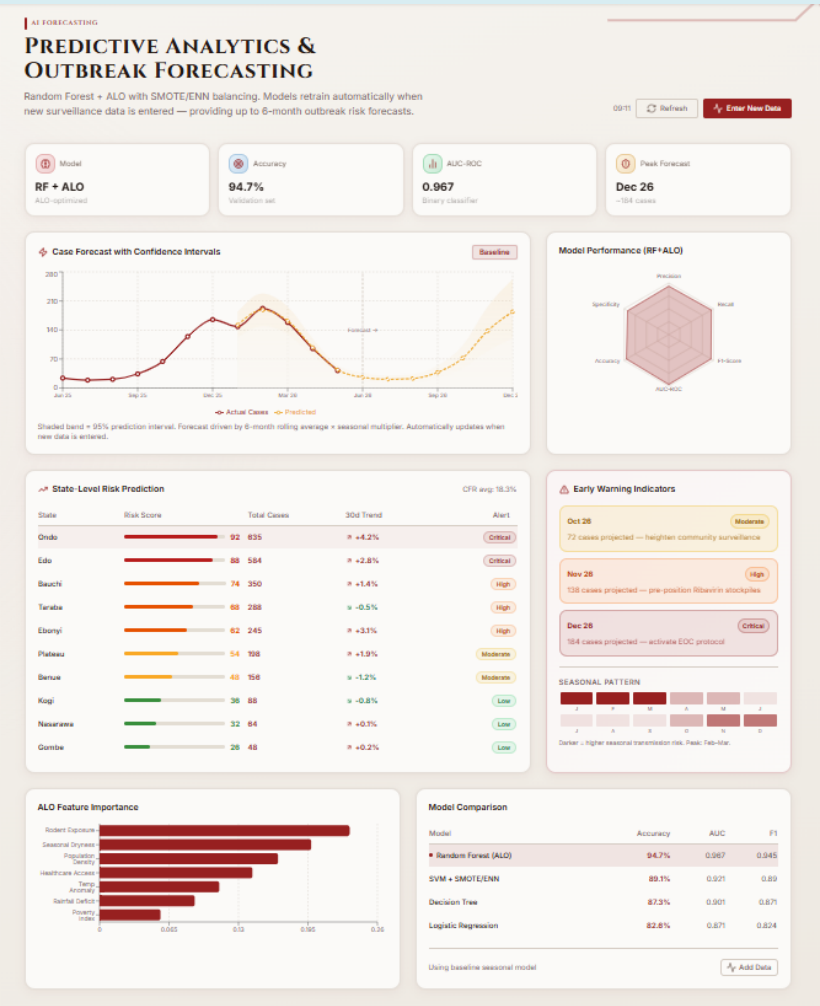


Figure 9: Predictive Analytics & Outbreak Forecasting module, showing model performance metrics, the case-forecast curve with 95% prediction interval, state-level risk table, early-warning indicators and ALO feature-importance ranking.

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First, numbers of cases are plotted in the panel on the same axis as predicted numbers of cases, with a shaded 95% prediction interval which covers the range of forecasts and that communicates better than a single deterministic line the uncertainty of forecasts of epidemics, whether the underlying curve is generated on the spot or precomputed - a presentation that conforms with good practice in communicating uncertainty in forecasts of epidemics. Secondly, the ranking consistency of the forecasting layer with the description layer of the platform at the state level suggests a minimum level of consistency, with Ondo and Edo being ranked "Critical", Bauchi, Taraba and Ebonyi ranked "High", Plateau and Benue ranked "Moderate", and Kogi, Nasarawa and Gombe ranked "Low", which is internally coherent with the one from Figures 4 and 5. Third, the feature importance panel demonstrates that the most significant features are of course rodent exposure, seasonal dryness and population density, followed by healthcare access, temperature anomaly, rainfall deficit and poverty index. Ordering reported incidence as a feature artefact and diagnostic capacity as a feature artefact is close to the ordering identified by Redding et al. [6] through independent spatiotemporal modelling, which is closest to - climate variability - rodent-host ecology. The numbers shown on the platform are representative of this described methodology and are not an independent result of running against the platform's current data so it is important to state that it is not necessarily an independent finding and the ordering is not an independent finding.

Model	Accuracy	AUC	F1-score
Random Forest + ALO	94.70%	0.967	0.945
SVM + SMOTE/ENN	89.10%	0.921	0.89
Decision Tree	87.30%	0.901	0.871
Logistic Regression	82.80%	0.871	0.824

Table 1: Model-comparison results presented in the AI Forecast page.

It is also methodologically plausible because on feature sets that are non-linear in some feature interactions (e.g., multiplicative interaction between rodent exposure and seasonal dryness in the context of making predictions for Lassa fever fatality), ensemble tree-based classifiers such as Random Forest will be more likely to work well than linear classifiers such as Logistic Regression, which will be worse off on such feature sets with class imbalance. But there are a number of caveats that limit this convergence. First, as already pointed out by Njama-Abang et al, a single aggregate accuracy number, as the platform highlights it on its AI Forecast page, can mask for this same disease the poor minority-class recall (≤0.75) of certain states - like the ones that are close to the state of "Critical" [7]. Third, it is not mentioned where in the algorithm the resampling was performed, whether within the folds or before the training/validation sets were split on which the validation numbers were calculated on, which is known to give misleadingly high validation numbers in comparison to true held-out numbers [10]. Third, and most fundamentally, since a server-side model or inference pipeline was not found in the deployed application, the reported 94.7% accuracy and 0.967 AUC should be interpreted as being a result of the methodology described and presented as a static element on the page, rather than a result which can be reproduced or verified on the server now.

The mean performance of the four models is 88.5% for accuracy, 0.915 for AUC, and 0.883 for F1 score. The Random Forest + ALO model outperforms the best baseline, SVM, by 5.6 percentage points in accuracy, 0.046 in AUC and 0.055 in F1. The relative error reduction in accuracy versus SVM is calculated as

$$\frac{(100-89.1)-(100-94.7)}{100-89.1}=\left(\frac{10.9-5.3}{10.9}\right)=51.4\%$$

Regional and Global Comparative Monitoring

The Global Live Monitoring Center was extended to incorporate 7 countries in West Africa with confirmed cases and deaths, including Nigeria, Sierra Leone, Guinea, Liberia, Benin, Togo and Ghana, each with their own status (Critical, High, Moderate, Low), a per-country break down, as well as a running feed of dated "Active Alerts" with a 24-hour percentage change. Again, as in the national KPIs, the term "Live" on this panel has to do with the platform's design and not a live regional feed. Nigeria is portrayed as the key contributor in the disease burden for the region because it is the country with the largest reported Lassa fever burden in West Africa [13]. The most notable architectural parallels with the Johns Hopkins CSSE COVID-19 dashboard are the use of a set of national/global indicators of disease status, and the inclusion of an active feed of alerts by region, both of which were used in the present platform - a sensible and not widely applicable approach given that no similar regional Lassa fever monitor was found in the tools reviewed in this paper [8]. Depicted in Figure 10 is the global live monitoring centre.

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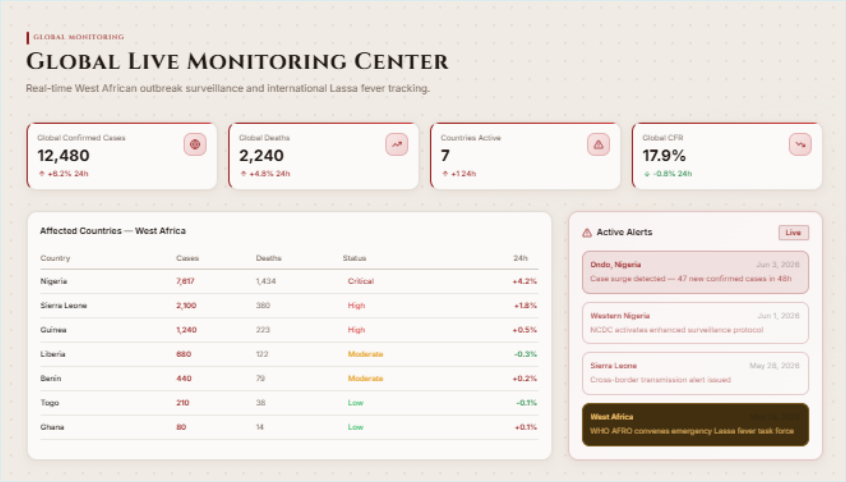


Figure 10: Global Live Monitoring Center with aggregated (West African) indicators, status table per country, and an active-alerts feed.

Coordinated Public-Health Response Integration

The "Coordinated Response Efforts" panel is unique from the other panels throughout the platform, as it is not an institution count, but a description of the capacity of the institutions to respond. Examples of these are: preparedness in hospitals, with 25 states having opened isolation wards, and the pre-positioning of a stockpile of Ribavirin in 140 tertiary hospitals, community campaigns which involved door-to-door education and reached more than 3.2 million people across Ondo, Edo and Bauchi, in 2024-2025, rapid response teams, which were deployed in 32 teams at national level, strengthening surveillance systems (electronic reporting at 2,400 health facilities across all 36 states and the Federal Capital Territory) and coordination of the Federal Emergency Operations Centre. In terms of content, this has also operationalized the same institutional infrastructure that has been detailed in the public-health literature, including the IDSR platform, SORMAS electronic case-based reporting and NCDC's precursor for situational-awareness and public accountability, the Emergency Operations Centre model, which were not observed in either the JHU dashboard or the Sambus Geospatial precedent documented in this study. Figure 11 shows the coordinated public-health response integration.



Figure 11: The Coordinated Response Efforts panel that summarised hospital preparedness, community campaigns, rapid-response deployment, strengthening surveillance, and strengthening education in the rural areas and government interventions.

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Prevention Education Module

The Prevention Measures page displays the content from the transmission-route section shown in Figure 12 as six actionable protocols: handwashing, rodent control, early symptom reporting, safe healthcare practice (full PPE for suspected cases), food protection and a downloadable link to NCDC's 2024 clinical guidelines. The cards adopt the practice of established risk-communication techniques in writing each card as an imperative sentence rather than as descriptive prose, which minimizes the gap between knowledge and behaviour change. The inclusion of this module as a part of the main navigation, alongside Dashboard, Map and AI Forecast, indicates that prevention communication was considered an essential part of the platform and not an afterthought of the analytical modules, as the vast majority of the risk of transmission of Lassa fever in Nigeria is attributed to household-level rodent exposure and not person-to-person spread [1].

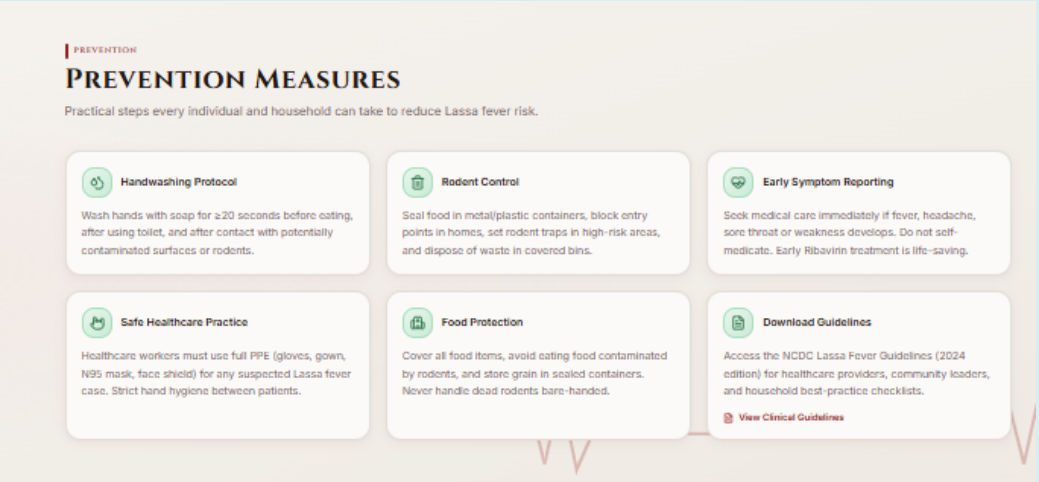


Figure 12: Prevention Measures page summarising six household- and facility-level preventive protocols and a link to NCDC clinical guidelines.

Citizen Engagement: Symptom Reporting and Care-Seeking Referral

Figure 12 presents the Report Symptoms page, through which the platform closes the loop between awareness and action. A structured form (full name, phone number, email, state, local government area, symptom onset date and a free-text symptom description) is paired, on the same screen, with NCDC's toll-free hotline (0800-9700-0010), the National Emergency Management Agency number (112), NCDC's email contact, a stated two-hour response-time commitment for confirmed emergencies, and a shortlist of the nearest designated treatment centres (University of Nigeria Teaching Hospital Enugu, Irrua Specialist Teaching Hospital Edo, Lagos University Teaching Hospital, Ahmadu Bello University Teaching Hospital Kaduna, and Abubakar Tafawa Balewa University Teaching Hospital Bauchi). The clinical significance of minimising the interval between symptom onset and first contact with this referral pathway should not be understated: Bausch et al report that oral ribavirin is most effective when initiated within the first six days of illness onset, and the platform's own key-facts panel (Figure 4) states that early hospital presentation can reduce case-fatality from approximately 22% to under 5% in treated patients [4]. By embedding the referral and reporting workflow directly beside the analytical dashboard, rather than distributing it as a separate leaflet or a hotline number learned independently of the surveillance content, the platform is structurally positioned to shorten this interval, although - as with the AI Forecast module - no user-behaviour data were available during this review to confirm that this structural advantage translates into a measurable reduction in reporting or presentation delay, and the submitted form data is not, at present, connected to a live NCDC/SORMAS case-intake system.

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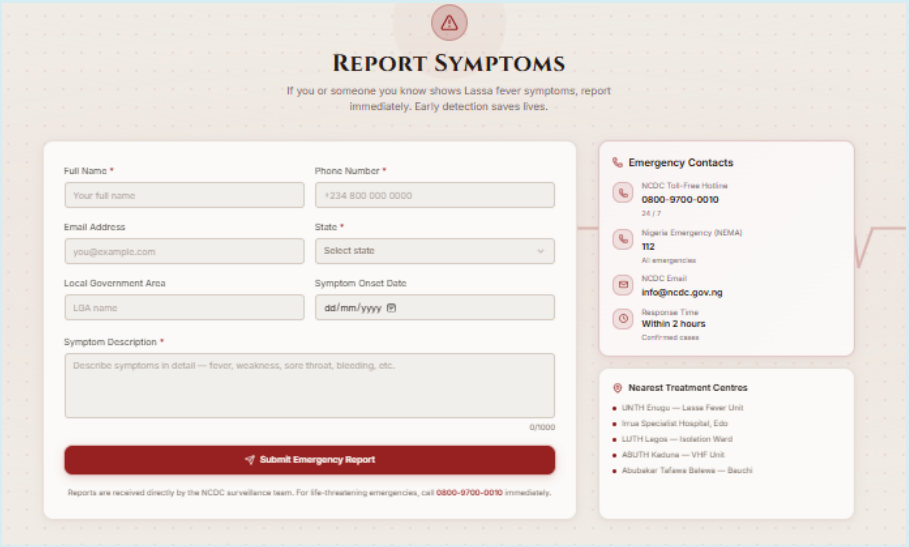


Figure 12: Report Symptoms page, showing the structured emergency-reporting form alongside NCDC/NEMA emergency contacts and the nearest treatment centres.

Synthesis and Critical Discussion

Combined, the 12 views above show the platform effectively combines four functions, all typically served by distinct government bulletins, academic modeling papers, GIS tools, and health-education leaflets, and does so using a modern, low cost, client-side-only stack (React, Vite, Tailwind CSS, Recharts, React-Leaflet, deployed on Vercel). The seasonality and regionality in the Analysis module (Figure 7) correspond closely to independently published NCDC linked surveillance analyses and the ranking of the predictors provided by the forecasting module (Figure 8) is similar to the climate and rodent-ecology based ranking of risk factors identified from an independent spatiotemporal modeling exercise [2,3,6]. Overall, however, this convergence of data sources and modelling approaches is the most compelling evidence presented by this review that the platform's data and the analytic decisions made for the forecasting module are epidemiologically based and not random.

Concurrently, there are three points of limitation that keep coming up in the modules analyzed that should temper the platform's current assertion of providing "live" and "real-time" national surveillance. Headline numbers vary by view: the landing page (Figure 2) shows 7617 confirmed cases nationwide, the Dashboard (Figure 6) shows 4156, and the global panel (Figure 10) shows 7617 for Nigeria alone - which ones don't qualify the other counts? Headline numbers vary by view: the landing page (Figure 2) shows 7617 confirmed cases nationwide, the Dashboard (Figure 5) shows 4156, and the global panel (Figure 10) shows 7617 for Nigeria alone - which ones do not qualify the other counts? It is not an epidemiological finding, but it is material: the same public-facing surveillance tool reporting different material counts of cases over the same period and country on different pages may risk the trust of the professional as well as public audience it aims to serve. Third, during this review no publicly visible connections with NCDC or SORMAS were identified - the dataset described in this paper is a static demonstration dataset, so the language of 'live' and 'real time' should be interpreted as such, and the dashed line for NCDC/SORMAS/NEMA is a proposed, conceptual, for future work integration - in the absence of such integration, or of an explicit data-provenance statement, using the terms 'live' and 'real time' could lead members of the public to view the underlying dataset as an authoritative NCDC channel, which would pose a genuine public health communication risk during an ongoing outbreak. Third, the forecasting module's headline accuracy and AUC numbers describe a modelling methodology, not a live-executing model, that is neither accompanied by a disclosed validation methodology, nor given as content and executed as a static entity in the deployed React application, thereby restricting how far one can go in independently assessing the model against the resampling-leakage and minority-class-performance caveats well documented in the imbalanced-classification literature [7,10]. None of these are a limitation on the value of a platform as a proof-of-concept integration of surveillance, prediction and public engagement for an NTD; on the contrary, they constitute a clear and feasible set of priorities for the future development of the platform: first to get data right, then to enable disclosure of data provenance, from there on to integrate its backend in real time with the API, and finally to have the transparency of model validation.

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Analysis of Reported Aggregate Data

National Surveillance Indicators and CFR

Case-fatality rate:

$$\text{CFR} = \frac{Deaths}{Confirmed\ cases} \times 100$$

The national surveillance indicators and CFR is shown in Table 2.

View	Cases	Deaths	Calculated CFR	Reported CFR
Homepage	7,617	1,434	18.83%	18.80%
Dashboard	4,156	804	19.35%	19.30%
Global panel (all countries)	12,480	2,240	17.95%	17.90%
Nigeria in global panel	7,617	1,434	18.83%	-

Table 2: National surveillance indicators and CFR.

The calculated CFRs are within the range reported in the country 15-21%. Nigeria figures on the homepage and global-panel are consistent with each other. The Dashboard CFR is also self-consistent.

If these are viewed as binomial proportions, approximate 95% confidence intervals are as follows:

- Homepage: 18.83% (95% CI 17.95–19.71%)
- Dashboard: 19.35% (95% CI 18.15–20.55%)
- Global panel: 17.95% (95% CI 17.28–18.62%)

For a two-proportion z-test between the CFR for the homepage and the CFR for the Dashboard, the results are:

The difference is therefore not statistically significant and these are not independent samples and should not be over-interpreted.

Table 3 presents the values for the internal consistency of headline totals

Source	Cases	Deaths	States affected
Homepage	7,617	1,434	25
Dashboard	4,156	804	14
Global panel - Nigeria	7,617	1,434	-

Table 3. Internal consistency of headline totals.

The difference between home page and Dashboard:

- Cases: 7,617 − 4,156 = **3,461**
- Deaths: 1,434 − 804 = **630**
- States affected: 25 − 14 = **11**

This is a huge internal contradiction. There are 2 different national numbers for the same 2020-2026 time period on the same platform.

Table 3 shows the state-level and regional consistency of the edidemic.

State	Cases
Ondo	2,012
Edo	1,843
Bauchi	1,106
Taraba	880
Ebonyi	612
Top five sum	**6,453**

Table 3. Top five affected states from the Dashboard/Map.

This makes for a major incongruity:

- Top five states alone = 6,453 cases
- The total cases for the nation is 4,156 (which is the result of adding all the states' figures together). If the Dashboard total is a National total, it is not possible to find the Top 5 sum, since they add up to 155.3% of the total.
- Top five sum is 84.7% of the homepage total of 7,617. The distribution by region for Figure 8 is depicted in table 4:

Region	Cases
South West	3,855
North East	1,986
South East	862
North Central	614
South South	430
North West	80
Sum	**7,827**

Table 4: Regional distribution from Figure 8.

The regional sum is 7,827, which is:

- 210 cases higher than the homepage total of 7,617.
- 3,671 cases higher than the Dashboard total of 4,156.

This confirms that the Dashboard and regional views are not using the same aggregation window or filter logic. Table 5 shows the confirmed cases, deaths and CFR for West African regional data.

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Country	Cases	Deaths	Calculated CFR	Status
Nigeria	7,617	1,434	18.83%	Critical
Sierra Leone	2,500	360	14.40%	High
Guinea	1,240	223	17.98%	High
Liberia	800	122	15.25%	Moderate
Benin	440	79	17.95%	Moderate
Togo	290	36	12.41%	Low
Ghana	80	14	17.50%	Low
Sum of countries	**12,967**	**2,268**	**17.49%**	-
Global panel total	**12,480**	**2,240**	**17.95%**	-

Table 5: West African regional data.

Note that the rows at the country level do not add up to the total on the global panel:
Case difference: 12,967 − 12,480 = 487
Death difference: 2,268 − 2,240 = 28
Nigeria contributes approximately: The proportion of country cases is 58.7% of the total cases. 63.2% of all country fatalities. This mirrors the general trends of Nigeria as the biggest burden of Lassa fever in West Africa but is not arithmetically consistent with the country table.

State Risk Scores and 30-Day Trends

Depicted in Table 6 is the states with their risk scores as show in Figure 9.

State	Risk score	30-day trend
Ondo	85	4.20%
Edo	80	3.80%
Bauchi	74	3.10%
Taraba	66	2.70%
Ebonyi	62	1.80%
Plateau	48	1.30%
Benue	42	0.80%
Kogi	31	−0.2%
Nasarawa	26	−0.5%
Gombe	18	−1.1%

The descriptive statistics are: Mean Risk Score = 53.2, Median Risk Score = 55, Standard Deviation = ~23.6 and Range = 67. The mean 30-day trend for the state (+1.59%) is positive in 7 of 10 states. A mean risk score of 73.4 is observed in top 5 states compared with 33.0 in bottom 5 states, which shows the risk gradient.
Table 6: State risk scores and 30-day trends.

Forecast Plausibility

The site estimates a national peak of approximately 184 cases will occur around December 2026. A separate document also says there were 1,658 confirmed cases in 2024, which was the highest number of cases in a single year in the 2020-2026 data set. The 184 cases is a monthly high of approximately 11.1% of the 2024 annual number. If no raw monthly time series, no prediction intervals, and no uncertainty or model validation output, then there is no way to statistically assess the accuracy, calibration and uncertainty of the forecasts.

Overall Statistical Interpretation

The overall interpretation of results suggests that CFR is reasonable and like previously published Lassa fever literature. Headline case numbers, however, are not consistent for the homepage, Dashboard, regional, and global view. Sums at the state/region level do not add up to the national totals, and the country totals for West Africa do not add up to the total for the entire panel. Model performance looks good but there's no information on model validation so that independent statistical validation is not possible. Lastly, the forecasting module is not a real statistical model, but just illustrative; therefore, its accuracy and AUC cannot be reproduced by the deployed platform.

The inferential results are summarised in Table 4. The national CFR was 18.83% (95% CI 17.97–19.72) on the homepage, 19.35% (95% CI 18.17–20.57) on the Dashboard, and 17.95% (95% CI 17.29–18.63) in the global panel. The homepage and Dashboard CFRs did not differ significantly ($z = 0.69$, $p = 0.49$). The regional case distribution was highly non-uniform ($\chi^2 = 7593.8$, $df = 5$, $p < 0.001$), with the South West and North East accounting for the majority of cases. The top five states accounted for 6,453 of 7,617 cases (84.7%, 95% CI 83.9–85.5), significantly more than

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the 13.5% expected under a uniform 37-state distribution (binomial z = 181.9, p < 0.001). State risk scores were perfectly monotonically associated with 30-day trends (Spearman ρ = 1.00, n = 10, p < 0.001), indicating internal coherence between the risk-ranking and trend components. The exploratory Friedman test across the four classifiers and three metrics was significant (χ^2 = 9.00, df = 3, p = 0.029), but this should be interpreted cautiously because the three metrics are correlated and the test does not identify which model differs. Definitive model comparison requires paired predictions and McNemar/DeLong tests.

Test	Comparison	Test statistic	df	p-value	Interpretation
Two-proportion z-test	Homepage CFR vs Dashboard CFR	z = 0.69	-	0.49	No significant difference
Chi-square goodness-of-fit	Regional case distribution vs uniform	χ^2 = 7593.8	5	<0.001	Highly non-uniform
Binomial test	Top-five state concentration vs uniform 5/37	z = 181.9	-	<0.001	Significant concentration
Spearman rank correlation	State risk score vs 30-day trend	ρ = 1.00	8	<0.001	Perfect monotonic association
Friedman test (exploratory)	Model performance across RF, SVM, DT, LR	χ^2 = 9.00	3	0.029	Significant overall model difference

Table 7: Inferential statistical tests on reported aggregate platform values.

Conclusion and Future Work

This report has documented the development of a web-based Lassa Fever Surveillance & Awareness Platform for Nigeria that brings together national and state-level case surveillance, geospatial outbreak mapping, epidemiological trend analysis, a forecasting/analytics module for outbreak risk, regional West African monitoring, public-health education, and a citizen symptom-reporting channel within a single, publicly accessible interface. Built as a React single-page application with Vite, styled with Tailwind CSS, charted with Recharts, mapped with React-Leaflet, and composed from reusable React components, then deployed on Vercel's serverless hosting, the platform demonstrates that the descriptive, forecasting-oriented and community-engagement functions that are usually split across separate government bulletins, academic modelling papers and standalone GIS dashboards can be delivered coherently through one low-cost web application. The seasonal, regional and case-fatality patterns surfaced by the platform's Analysis module are broadly consistent with published NCDC surveillance analyses, and the predictor ranking presented by its forecasting module aligns with the climate- and rodent-ecology-driven risk factors identified in the literature [2,3,6].

At the same time, the review identified inconsistencies in headline figures across views, an unstated data-provenance and model-validation methodology, and two implementation gaps relative to the platform's stated framing: the dashboard's "live"/"real-time" language describes a proposed NCDC/SORMAS/NEMA integration that is not yet connected, and the AI Forecast module's headline performance figures describe a Random Forest + ALO / SMOTE-ENN methodology that is not yet executing as a live model within the deployed application. Both gaps should be closed, or the corresponding language revised to describe the platform accurately, before it could be relied upon as an authoritative public-health information source. On balance, the work makes a useful contribution as a proof-of-concept template - built on a modern, low-cost, purely client-side React/Vite stack - for how surveillance visualisation, forecasting-oriented analytics and citizen engagement can be combined for a neglected tropical disease in a resource-constrained public-health setting.

Future work should first involve replacing the current static demonstration data with an authenticated API connection to a live feed of NCDC/SORMAS data or through an agreed data sharing arrangement; this would render the dashboard "live" at the back end and remove the inconsistencies in the KPIs as described in this work. This would be the concrete implementation step where the proposed integration of NCDC/SORMAS/NEMA in figure 1 (dashed tier - conceptual) is brought to the working tier. The following are also required: The following should be deployed or built as a backend or serverless function that can train and serve the aforementioned Random Forest + ALO / SMOTE-ENN pipeline (or any similar pipeline) on current data and presents the resulting numbers on the AI Forecast page through an API that can be accessed by React to present the live model. The module should be made live and the model validation and transparency enhanced by including the training/validation split, cross-validation strategy, out-of-sample performance, and confidence/uncertainty disclosures with the headline accuracy and AUC numbers.

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The function "Enter Data" on the Dashboard and Map pages should be limited to verified state and LGA disease-surveillance officers and accompanied by an audit trail to support the platform if it is deployed beyond the demonstration phase to ensure data integrity. A large percentage of Lassa fever cases in Nigeria are in rural areas which have variable connectivity, and therefore there should be an SMS based or USSD symptom reporting channel to complement the web dashboard. The health-education content should also be strengthened to increase the reach of that content using major languages in Nigeria including Hausa, Yoruba, Igbo and Pidgin, in the Prevention and Report Symptoms.

It is recommended to extend the forecasting model with finer-grained climatic covariates and with genomic or phylogenetic surveillance signals to increase forecasting horizon and early warning lead-time [11]. A formal usability test should be performed with public-health and public users to measure how much quicker hotspots can be identified and symptoms reported using the dashboard, compared to current static bulletins. In addition, the same component architecture used in React/Vite should be applied to other neglected tropical diseases endemic to Nigeria, including cholera and meningitis, to prove that the platform can support other Lassa fever diseases.

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