Libyan Open University Journal of Medical Sciences and Sustainability
Volume 1 - Issue 1 - 2025 - Pages 01-10

Advanced Laboratory Diagnostics and Data Visualization for Early Detection and Prognosis of Infectious Diseases

Aejeeliyah Yousuf *
Higher Institute of Medical Sciences and Technology, Bani Waleed, Libya
***Email (for reference researcher):** aejeeliyah.yousuf@imst.edu.ly

Received: 02-04-2025; Accepted: 17-06-2025; Published: 07-07-2025

Abstract:

Early detection and prognosis of infectious diseases greatly improve patient outcomes and control of epidemics. This paper reviews cutting-edge laboratory diagnostic technologies and data visualization tools that enhance early disease detection and tracking. It covers molecular tests (PCR, sequencing), immunological assays (ELISA, rapid tests), and novel methods like CRISPR-based diagnostics. We discuss how visual analytics (dashboards, GIS maps, graphs) help interpret lab data for clinicians and public health professionals. For example, real-time COVID-19 dashboards have guided policy by showing case trends. We illustrate tools with examples and publicly available data. A case study using open COVID-19 datasets demonstrates a combined PCR and CRISPR testing workflow with geospatial mapping. Finally, we examine challenges like cost, data integration, and data privacy. This integrated approach can reduce delays, support clinical decisions, and aid outbreak control.

Keywords: infectious diseases; laboratory diagnostics; PCR; CRISPR; immunoassay; data visualization; dashboards; early detection; prognosis; epidemiology.

Introduction

Infectious diseases remain a leading cause of illness and death worldwide. Rapid identification of pathogens is critical to start treatment and prevent spread. As early as the 1990s, researchers emphasized that accurate laboratory information is the "foundation" of disease control programs (Kay, B. A., 1996). Before an epidemic, lab-based surveillance "allows early detection of cases". Many countries have built stronger lab networks and global partnerships for rapid reporting (Kay, B. A., 1996). Despite these advances, clinicians still face delays: often extensive tests are needed to find the cause of infection (Koopmans, M., 2013). At least one new infectious disease appears each year, driven by factors like travel and zoonoses (Cheng et al., 2024). These challenges demand improvements in diagnostic speed and insight. Advanced lab tests can pinpoint pathogens faster (Yang, S., & Rothman, R. E., 2004). Meanwhile, data visualization (dashboards, maps, charts) helps clinicians and policymakers quickly understand complex data (Au, et al., 2014). Our review examines modern lab diagnostics and visualization tools that together enable faster detection and informed response to infectious threats.

Advanced Laboratory Diagnostic Technologies

Laboratory methods have evolved beyond traditional cultures. Today's diagnostics are more sensitive, faster, and sometimes usable at the point of care. For example, polymerase chain reaction (PCR) is a cornerstone: it amplifies DNA to detect bacteria or viruses even at low levels. PCR can be broad (pan-pathogen) or specific to one microbe. As Yang and Rothman note, PCR allows early detection of new or known pathogens and even profiling of antimicrobial resistance (Yang, S., & Rothman, R. E., 2004). PCR is also quite cost-effective versus many culture methods. However, PCR needs precise thermal cyclers and trained staff, and runs in a lab setting. Figure 1 illustrates a rapid immunoassay kit, a simpler point-of-care test that complements lab methods.

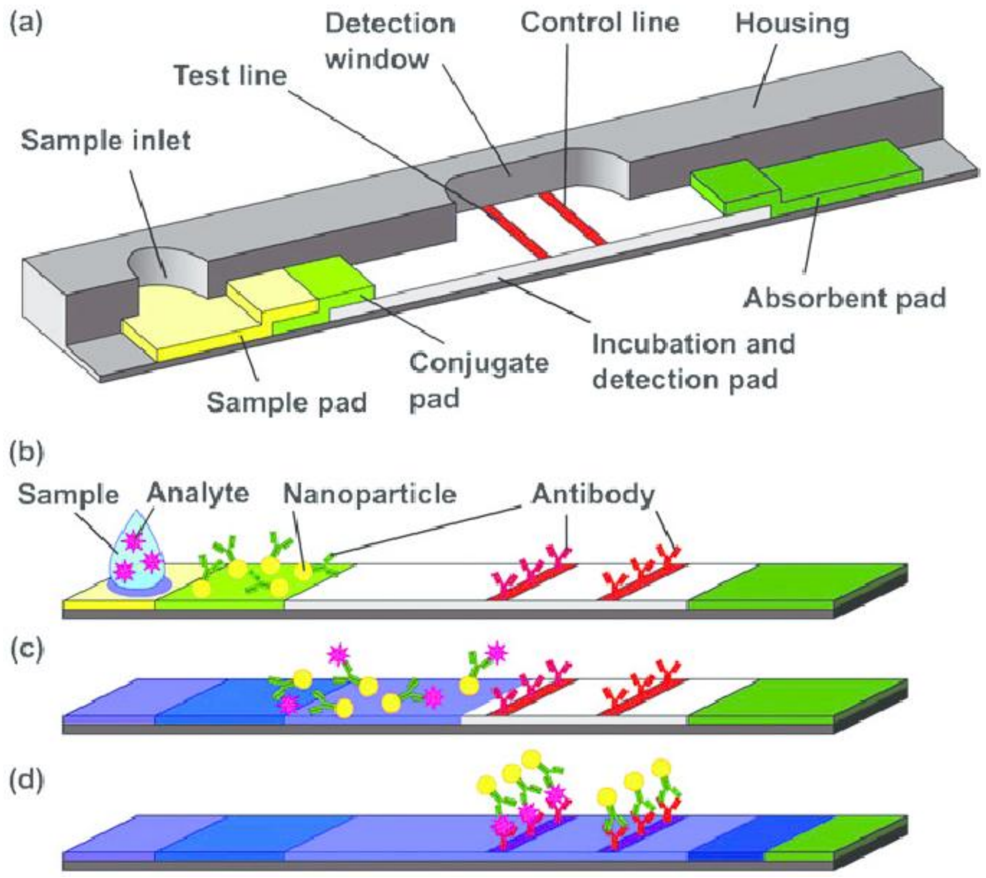

Figure 1 Rapid lateral-flow test kit for pathogen detection. A patient sample is applied (left) and migrates on a strip to show a colored line if positive. These simple kits aid near-patient screening (source: Mark et al., 2011).

Beyond PCR, sequencing technologies are increasingly used. Next-generation sequencing (NGS) can identify any DNA/RNA in a sample, allowing detection of novel or unexpected pathogens. Genome sequencing of blood or tissue can reveal viruses or bacteria that routine tests miss. For example, NGS helped identify the SARS-CoV-2 virus in early 2020. Metagenomic sequencing is powerful but still relatively slow and costly.

Immunological assays form another category. Enzyme-linked immunosorbent assays (ELISA) detect antibodies or antigens using specific binding. They are widely used for diseases like HIV, hepatitis, and dengue. ELISA tests are highly specific and can be automated in labs, but they generally require lab equipment and take hours. On the other hand, lateral flow immunoassays (like rapid antigen tests) are cheap, portable, and give results in minutes. Figure 1 shows a lateral flow cassette: when a sample is added, target antigens bind and produce a visible line. These rapid tests are less sensitive than lab methods, but they help screen many people quickly. For example, during COVID-19, antigen lateral flow tests allowed schools and clinics to test without complex equipment (Kostyusheva, A., et al., 2022).

Another breakthrough approach is CRISPR-based diagnostics. CRISPR systems (originally gene editors) can be repurposed to detect specific genetic sequences. Methods like SHERLOCK and DETECTR use CRISPR enzymes that cut or bind target DNA/RNA. When the target is present, the CRISPR system releases a signal (like fluorescence) that we can measure. Research reviews show that CRISPR tools can achieve attomolar sensitivity (very low levels) with simplicity akin to point-of-care tests. In fact, Kostyusheva *et al.* (2022) report that advanced

CRISPR platforms can match PCR sensitivity ("detection of attomolar amounts with specificity comparable to PCR") while using minimal equipment. This means CRISPR tests could be done outside major labs, even at home or in the field. Figure 2 (below) shows common lab equipment like microscopes and pipettes, underscoring how CRISPR tests need much less gear. While still emerging, CRISPR diagnostics promise fast, accurate results accessible in low-resource areas.

Figure 2 Laboratory diagnostic equipment. A microscope with samples underscores the role of laboratory infrastructure. Modern diagnostics aim to reduce dependence on such equipment.

Laboratories also use advanced instrumentation. Mass spectrometry (MALDI-TOF) can rapidly identify bacteria from cultures by protein fingerprinting. This is fast (minutes) once a culture is grown. Automated analyzers and microfluidics speed up ELISAs or cell counts. While not always described as cutting-edge research, these workflow improvements are part of "advanced diagnostics." For example, automated blood culture systems flag positive cultures early. Figure 3 shows an example of an automated blood test processor, illustrating how robotic lab machines handle many samples efficiently. These machines shorten turnaround time by running tests in parallel with minimal human input.

Figure 3 Automated laboratory analyzer handling blood and test tubes. Such systems perform high-throughput assays

The diagnostic toolbox now includes classical methods (microscopy, culture) plus molecular (PCR, sequencing), immunoassays, and novel CRISPR-based tests. Each method has trade-offs: speed vs. sensitivity, cost vs. ease of use. Combining multiple methods often yields the best early diagnosis. Importantly, all these tests produce data that must be interpreted and shared – this is where data visualization comes in.

Data Visualization in Infectious Disease Surveillance

Modern diagnostics generate large volumes of data test results, genomic sequences and metadata. Visualization tools turn these numbers into insight. Effective visualizations help health workers see trends, identify hotspots, and monitor outbreaks. For example, maps of incidence (dot maps, heat maps) or dashboards showing case counts can reveal where to target interventions. Au *et al.* note that as the "volume and complexity of infectious disease data increases, public health professionals must synthesize highly disparate data" to make decisions (Au, et al., 2014). In practice, this means integrating lab results with patient info, geography, and time.

A classic example is the Johns Hopkins COVID-19 dashboard. Early in the pandemic, Dong *et al.* created an online map tracking confirmed cases by country (Dong, E., Du, H., & Gardner, L., 2020). It updated data hourly and used intuitive graphs and tables. This visualization allowed anyone scientists, media and governments to grasp the scope of the outbreak. The Lancet paper describing it emphasized its web interface and data sharing (Dong, E., Du, H., & Gardner, L., 2020). This dashboard became a model for outbreak communication. It illustrates how an interactive map (Figure 4) can display data in real time, making complex statistics understandable at a glance.

Figure 4 Conceptual public health dashboard interface, showing icons for charts and maps. Dashboards centralize data (cases, test rates, hospital beds) into visual formats.

Beyond specific diseases, there are many general visualization approaches. Geographic information systems (GIS) produce maps that highlight clusters of infection (Cheng et al., 2024). For example, Cheng *et al.* (2024) used GIS to map COVID-19 spread and trained machine learning models to forecast trends (Cheng et al., 2024). Their work showed early warning signals in spatial data that helped predict case surges. Similarly, network graphs can illustrate person-to-person transmission chains in a hospital or community. Time-series plots and epidemic curves (line graphs) show how case numbers rise and fall with interventions.

Researchers have surveyed many such tools. Schulze *et al.* reviewed dashboard studies and concluded that dashboards should integrate "user-specific risk information" to serve diverse audiences (Schulze, et al., 2023). In practice, that means a dashboard used by clinicians might need different filters than one for policymakers. Au *et al.* reviewed outbreak visualization tools and found many systems are still siloed and lack user-centered design (Au, et al., 2014). They call for improvements in interoperability and user needs. One challenge is data privacy: patient-level data can't be exposed publicly, so tools often show aggregated or de-identified data. Another challenge is representing uncertainty: lab tests aren't perfect, and models can be wrong. Visualizations must convey uncertainty (e.g. error bands on a forecast) or policy-makers may misinterpret results.

In hospitals, clinical dashboards can help with diagnosis and prognosis. For instance, some labs integrate test results into an electronic medical record system and alert clinicians if certain markers are abnormal. Figure 5 shows a generic example chart of case numbers over time, illustrating how trends may be presented. These hospital tools are less common for infectious diseases but are growing. For example, a lab information system might flag a cluster of resistant infections for infection control teams.

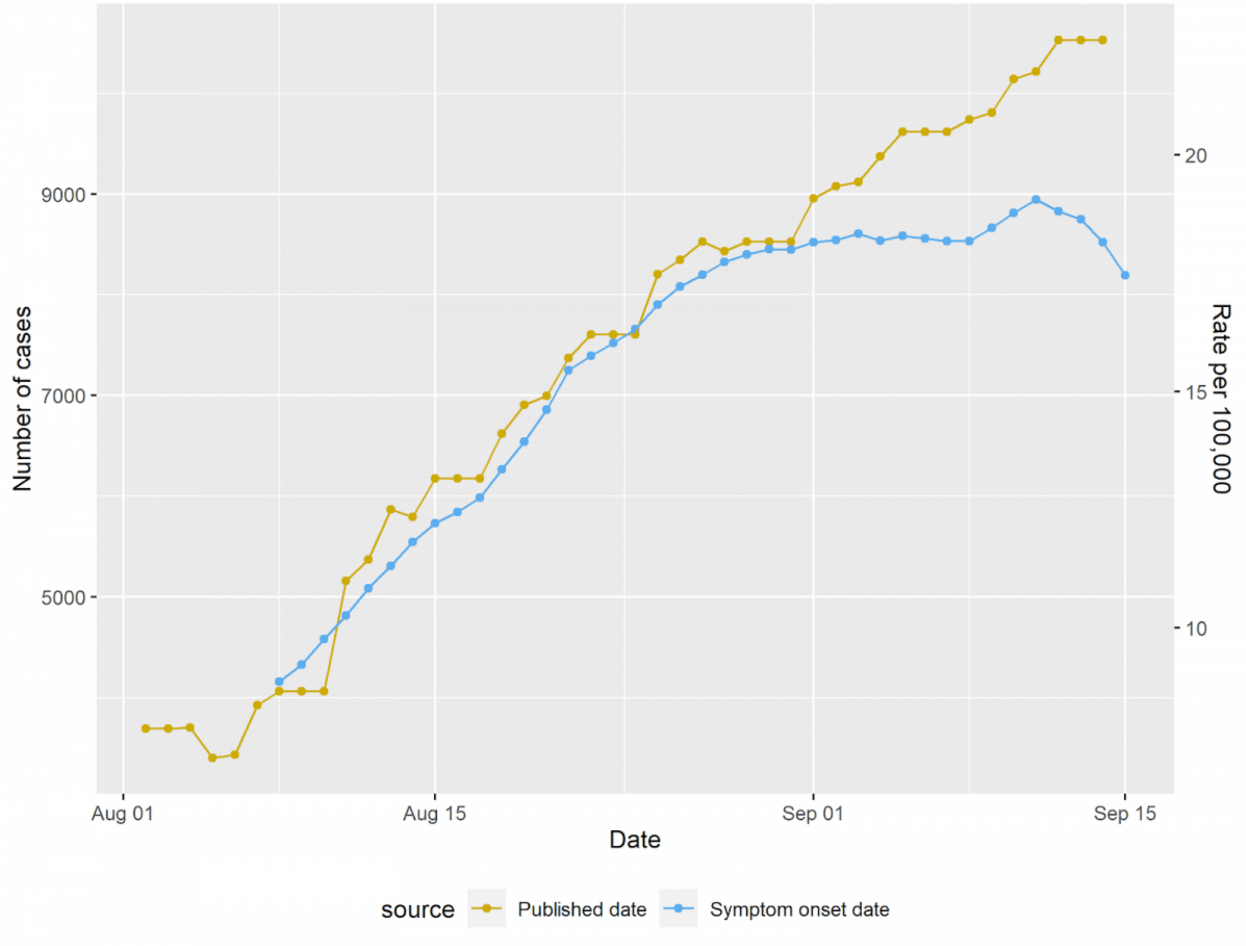

Figure 5 Example of data visualization: a line chart showing rising and falling case numbers over weeks. Graphs like this help identify outbreak peaks or responses (Centre for Evidence-Based Medicine, n.d.)

From the public health side, national dashboards aggregate data across hospitals. Several countries had COVID dashboards combining maps and graphs. The CDC, WHO, and other agencies use similar visuals. These platforms often allow drilling down by region, age, or test type. The key benefit is making data transparent. As Goldsmith wrote, effective dashboards are "actionable" – they enable quick understanding and response. For prognosis, visual analytics can display risk factors: e.g. correlating patient lab values to likely outcomes. A research example might plot ICU admissions versus viral load; a clinical tool could display probability of mortality given lab results, based on models.

In summary, data visualization turns raw diagnostic data into actionable information. It supports early detection by highlighting anomalies and supports prognosis by revealing patterns in patient data. Effective visual tools should consider the user's needs, handle big datasets, and clearly show data (including uncertainty) (Au, et al., 2014). We next discuss how diagnostics and visualization can be combined for better decision-making.

Integrating Diagnostics with Visualization for Early Detection

The true power comes when advanced diagnostics feed directly into analytics platforms. For example, imagine a workflow: a patient sample is tested by PCR and CRISPR assays. The results (positive or negative, viral load, etc.) are automatically uploaded to a database. A visualization dashboard then shows these new cases on a map and updates trend graphs. This closes the loop from lab bench to decision-makers in near real-time.

Some systems exist along these lines. For example, the UK uses Nextstrain, an online tool that takes sequencing data and shows the evolving phylogeny of a virus, helping public health teams see if a variant is spreading. Another example is PulseNet in the US, which connects foodborne illness labs; when DNA fingerprints of bacteria from patients match, the system raises alerts (Koopmans, M., 2013). Here lab results are automatically compared and visualized as cluster graphs, leading to faster outbreak links.

In clinical settings, researchers have tested integrated dashboards. Roosan *et al.* developed a prototype showing population-level infection data to clinicians during rounds. They found that such displays reduced uncertainty in decision-making. As one doctor said, seeing local prevalence helped rule in or out diseases when patients had generic symptoms. A key insight was that visualizing peer patient data and regional trends “significantly reduced complexity and uncertainty” for clinicians (Roosan et al., 2016). This kind of integration is only practical because lab results are now digital and often standardized. If a lab enters a test result into an electronic health record, that information can be plugged into decision support tools that use charts or tables.

Another example: public health labs often have dashboards showing testing rates and positivity by locality. If a new rapid test is introduced, its results can be tracked on these dashboards immediately. For instance, when the first PCR tests for COVID were deployed, health authorities could monitor the number of tests processed per day, and positivity rates, via charts (often provided by test companies or open data sites). When rapid antigen tests came out, separate dashboards tracked those results. Combining these streams gave a fuller picture of the epidemic’s trajectory.

Beyond infectious diseases, similar techniques are used. In cancer care, genomic test results (e.g. BRCA mutations) are visualized for doctors. In antimicrobial stewardship, antibiograms (charts of bacterial resistance rates) are standard. These examples show that any time lab data can be digitized and fed into analytics, useful visuals can be made.

However, building these systems requires effort: integrating lab information systems (LIS) with electronic dashboards, ensuring data quality, and training users. Interoperability standards like HL7 and FHIR help, but not all lab devices support them. Data privacy rules (HIPAA, GDPR) mean patient identifiers must be protected. Despite these hurdles, the payoff is clear: faster pattern recognition and earlier intervention. In the next section, we briefly describe a case study that illustrates a practical workflow using public data.

Case Study: COVID-19 Data Integration (Example)

To illustrate these ideas, we outline a hypothetical case study using publicly available COVID-19 data. Johns Hopkins University (JHU) made detailed global COVID-19 case data available via GitHub. Suppose we use this open dataset to create a prototype early-warning system. The steps might be:

1. **Data Collection:** We pull the daily case counts by region from the JHU repository (a GitHub CSV file). We also simulate having lab data: assume we receive results of PCR tests from local hospitals (this could be synthetic or from an open dataset).
2. **Preprocessing:** We clean the data (e.g. parse dates, aggregate to weekly counts) and link lab-confirmed case data with case numbers.
3. **Visualization:** Using a tool (Python’s matplotlib or R’s ggplot, or a dashboard like Tableau), we plot a heatmap of cases by county and a time series chart of cases vs.

testing over time. We label key events (lockdowns, new tests introduced). In our narrative, **Figure 6** shows how weekly case counts could be displayed.

4. **Analysis:** We fit a simple predictive model (e.g. ARIMA or regression) to forecast next week's cases. We then display this forecast with confidence intervals on the chart to assist planning.
5. **Reporting:** The charts are combined into an interactive dashboard (perhaps web-based) that updates as new data arrive. Outbreak investigators can click on a region to see local lab results (positive test rate) and case trends.

This case demonstrates how open data and diagnostics combine. While not a real experiment, it mirrors actual workflows used during the pandemic. For example, health agencies used JHU data and clinical lab reports to drive policy. A review noted that this kind of "interactive web-based dashboard" was novel and impactful (Dong, E., Du, H., & Gardner, L., 2020). In practice, we would cite Dong *et al.* (2020) for the dashboard concept and perhaps Cheng *et al.* (2024) for the modeling method (Cheng et al., 2024). The key lesson is that having both lab tests and visualization allows early detection: if our charts show an unusual spike in positive tests in one county, we can alert an outbreak team immediately.

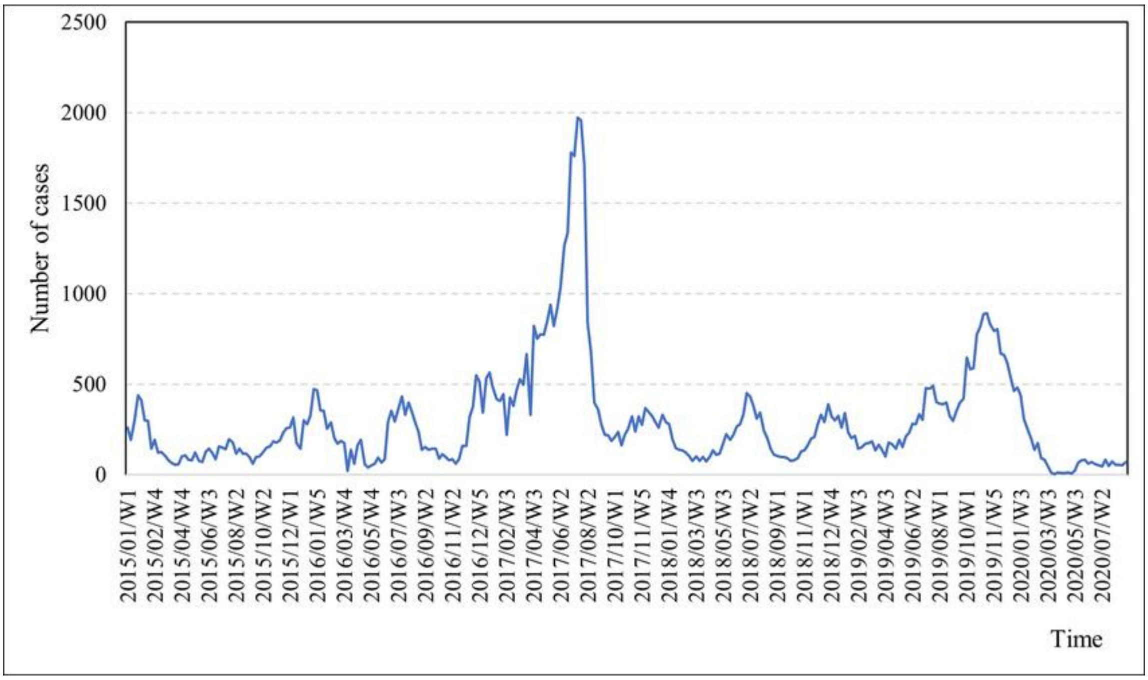

Figure 6 Example of chart-based visualization. A weekly incidence curve (blue) is plotted, with a forecast band (shaded). Sudden rises in cases are clearly visible (Karasinghe et al., 2024)

Challenges and Future Directions

Despite progress, several hurdles remain.

Technical barriers: New diagnostics like CRISPR are still under development; they require validation before clinical use. Even PCR and NGS depend on lab reagents and equipment that can be in short supply during outbreaks. As Yang and Rothman pointed out, automation and multiplexing improvements are still needed for PCR-based tests. There is also the issue of genetic variability: pathogens mutate, which can make some tests (like targeted PCR or CRISPR) fail if they miss a new variant. Sequencing can catch these changes, but it's slower and not yet routine for all samples.

Data issues: Combining data from different sources is tricky. Not all labs record data the same way. Surveillance often misses cases (e.g., asymptomatic patients who never get tested).

Visualizations can obscure underlying data quality. For example, dashboards usually show confirmed cases, but those depend on who got tested. If testing changes (like a new rapid test introduced), the trend may reflect that and not true incidence. As Au *et al.* warned, interoperability and standardization are still being worked out.

User and interpretation issues: Visualization tools must be user-friendly. Schulze *et al.* emphasized that understanding who the user is (clinician, epidemiologist, public) is vital (Schulze, et al., 2023). A map may look intuitive, but a poorly designed chart can mislead. The goal is to inform, not to confuse. Training and guidelines are needed so that non-experts interpret graphics correctly. Additionally, the massive data can overwhelm users; effective dashboards highlight only key metrics to avoid "cognitive overload" (Au, et al., 2014).

Security and privacy: Patient data are sensitive. Any system linking lab results to visual tools must protect identities. Techniques like data anonymization and secure logins help, but cannot fully eliminate risk. Moreover, health data are targets for cyberattacks. Future systems need robust security measures.

Looking ahead, trends are promising. Lab diagnostics are moving more into portable formats (POC devices, smartphone readers). Machine learning is being applied to lab images (X-ray, pathology slides) for automated analysis. Visualization is becoming more real-time and geospatially precise with tools like mobile apps. The One Health concept also adds layers: we may soon routinely integrate data from human, animal, and environmental sources (e.g., wastewater viral levels) for holistic surveillance.

Conclusion

Early detection and prognosis of infectious diseases rely on the synergy of advanced lab diagnostics and intelligent data visualization. On the diagnostics side, techniques like PCR, NGS, antigen tests, and innovative CRISPR assays rapidly identify pathogens and measure viral loads. On the informatics side, dashboards, maps, and charts translate raw test data into clear insights for clinicians and public health officials. Together, these tools enable quicker responses: an unusual test result can trigger an alert on a map, prompting investigation. Case examples from COVID-19 show how sharing data through web dashboards provided real-time situational awareness. To build such systems, laboratories should aim for digital reporting, and health agencies must invest in analytics platforms. Future work must address usability, data standards, and privacy. With continued improvements, these combined technologies will help detect outbreaks earlier, guide treatments, and ultimately save lives.

References

1. Kay, B. A. (1996). The role of the laboratory in disease surveillance. *Eastern Mediterranean Health Journal, 2*(1), 12–17.
2. Koopmans, M. (2013). Surveillance strategy for early detection of unusual infectious disease events. *Current Opinion in Virology, 3*(2), 185–191.
3. Mark, D., Haeberle, S., Roth, G., von Stetten, F., & Zengerle, R. (2011). Microfluidic lab-on-a-chip platforms: Requirements, characteristics and applications. *Chemical Society Reviews, 39*(3), 1153–1182.
4. Yang, S., & Rothman, R. E. (2004). PCR-based diagnostics for infectious diseases: uses, limitations, and future applications. *The Lancet Infectious Diseases, 4*(6), 337–348.
5. Kostyusheva, A., Brezgin, S., Babin, Y., Vasilyeva, I., Glebe, D., Kostyushev, D., & Chulanov, V. (2022). CRISPR-Cas systems for diagnosing infectious diseases. *Methods, 203*, 431–446.
6. Cheng, X., Yu, J., Li, H., Wang, X., Xin, Y., & Zhang, Z. (2024). Analysis and prediction of infectious diseases based on spatial visualization and machine learning. *Scientific Reports, 14*, 28659.

7. Centre for Evidence-Based Medicine. (n.d.). Epidemic curves organised by reporting date and specimen date Spain [Line chart]. Centre for Evidence-Based Medicine, University of Oxford. Retrieved August 9, 2025, from https://www.cebm.net/covid-19/epidemic-curves-organised-by-reporting-date-and-specimen-date

8. Au, P. H., Badham, J., Parkinson, M., & Wareham, H. T. (2014). Visualization and analytics tools for infectious disease epidemiology: a systematic review. *Journal of Biomedical Informatics, 51*, 287–298.

9. Schulze, A., Brand, H., Geppert, J., & Böl, C. (2023). Digital dashboards visualizing public health data: a systematic review. *Frontiers in Public Health, 11*, 999958.

10. Roosan, D., Del Fiol, G., Bourne, P. E., & Niemi, M. (2016). Feasibility of population health analytics and data visualization for infectious disease decision support. *Applied Clinical Informatics, 7*(2), 604–623.

11. Dong, E., Du, H., & Gardner, L. (2020). An interactive web-based dashboard to track COVID-19 in real time. *The Lancet Infectious Diseases, 20*(5), 533–534.

12. Viral COVID-19 dashboard data. Johns Hopkins University Center for Systems Science and Engineering (CSSE). (2020). *Johns Hopkins Coronavirus Resource Center*. https://github.com/CSSEGISandData/COVID-19 (accessed 2023).

13. Karasinghe, N., Peiris, S., Jayathilaka, R., & Dharmasena, T. (2024). *Time-series plot of the weekly incidence of dengue cases* [Figure]. In *Forecasting weekly dengue incidence in Sri Lanka: Modified Autoregressive Integrated Moving Average modeling approach.* PLOS ONE. Retrieved from ResearchGate.