

Predictive Analytics framework for real-time surveillance of Antimicrobial Resistance in Food systems

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Abstract

Antimicrobial resistance (AMR) poses a looming threat to global health, undermining decades of progress in human and veterinary medicine. In the United States, livestock production accounts for over 70% of medically important antimicrobial use, fueling the emergence of resistant pathogens that can transfer to humans through the food chain and environment. Existing surveillance mechanisms, such as the National Antimicrobial Resistance Monitoring System (NARMS), offer retrospective insights with significant delays, limiting timely intervention. We propose a Predictive Engineering Framework that integrates IoT-enabled farm sensors, veterinary prescription records, and environmental sampling into a centralized real-time surveillance platform. By applying Long Short-Term Memory (LSTM) networks for trend forecasting and Random Forest classification for hotspot detection, our system achieves a 0.7% mean absolute error in 14-day resistance forecasts and 85% classification accuracy for high-risk events. Pilot deployments on ten Midwestern hog farms demonstrated a 22% reduction in antimicrobial use and an 18% decrease in clinical resistance incidents over six months. This framework delivers actionable insights via interactive dashboards and automated alerts, enabling proactive antimicrobial stewardship and rapid outbreak response. National-scale adoption promises to save \$75 million annually in livestock antimicrobial expenditures and reduce human healthcare costs by \$200 million through early resistance mitigation. We recommend integrating this platform into USDA and CDC surveillance programs to safeguard U.S. food security and public health.

Keywords: Antimicrobial Resistance (AMR); Predictive Analytics; Livestock Surveillance; Real-Time Monitoring; Machine Learning in Agriculture; Public Health Informatics

1. Introduction

Antimicrobial resistance (AMR) represents a “slow-moving pandemic” that undermines decades of medical and agricultural progress (Smith et al., 2024). The Centers for Disease Control and Prevention (CDC) estimates over 35,000 annual U.S. deaths from drug-resistant infections, with \$4.6 billion in healthcare costs (CDC, 2019). Livestock production is a critical AMR driver: more than 70% of medically important antimicrobials are administered to food-producing animals, creating selective pressure for resistant strains that can transfer to humans via food and environmental pathways (FDA, 2023). Traditional surveillance—such as the CDC’s NARMS and FDA’s annual antimicrobial sales

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reports—operates on delayed reporting cycles and lacks predictive capabilities needed for rapid response (CDC, 2022; FDA, 2023).

To address these limitations, we developed a Predictive Engineering Framework for real-time AMR surveillance in U.S. livestock systems. Grounded in systems engineering and advanced data science, the framework integrates continuous data streams from farm-level sensors, veterinary prescription records, and environmental sampling into a centralized analytic platform (Jones et al., 2023). By coupling this data with machine learning algorithms—LSTM networks for forecasting resistance trends and Random Forest classifiers for hotspot detection—stakeholders can anticipate emerging resistance events with high accuracy and enact targeted interventions before outbreaks escalate (Zhao & Nguyen, 2023; Iledare, 2025).

2. Materials and Methods

2.1. System Architecture: The surveillance system is built on a three-tier architecture

Data Ingestion Layer: Utilizes MQTT protocols to collect 15-minute interval data from IoT-enabled sensors (temperature, humidity, animal movement), veterinary prescription APIs, and laboratory resistance test results (White et al., 2023).

Analytics Layer: Implements LSTM and Random Forest models using Python's Scikit-learn and TensorFlow libraries. LSTM networks predict resistance prevalence with a mean absolute error (MAE) of 0.7% and R^2 of 0.82, while Random Forest classifiers achieve 85% accuracy and an area under the curve (AUC) of 0.91 (Zhao & Nguyen, 2023).

Visualization Layer: Features a React.js and D3.js dashboard offering geospatial mapping, time-series plots, and automated SMS/email alerts for threshold breaches (Perez et al., 2022).

2.2. Data Collection and Preprocessing

Data from ten representative hog farms in Iowa were processed as follows:

- **Anomaly Detection:** Adaptive threshold methods removed sensor noise (Roberts & Wang, 2022).
- **Missing Data Imputation:** K-nearest neighbors imputed missing prescription entries (Troyanskaya et al., 2001).
- **Normalization:** Z-score scaling controlled for inter-farm variability (Iledare, 2025).

2.3. Predictive Modeling

Temporal Forecasting: LSTM models trained on sliding windows of 30 days to forecast 14-day resistance prevalence. Hyperparameters were optimized via grid search with 5-fold cross-validation (Yu et al., 2023).

Hotspot Detection: Random Forest classifiers with 50 decision trees identified high-risk farms. Feature importance analysis revealed antimicrobial usage rate, ambient temperature, and prior resistance prevalence as top predictors (Iledare & Smith, 2023).

2.4. Pilot Deployment

From June to November 2023, the system was deployed on ten Midwestern hog operations. Weekly feedback sessions with farm managers refined alert thresholds. Interventions included adjusted antimicrobial dosing and enhanced biosecurity measures within 48 hours of high-risk alerts.

3. Results

The pilot deployment of our real-time AMR surveillance system across five livestock farms demonstrated a clear and consistent reduction in antimicrobial resistance prevalence. Table 1 summarizes the AMR rates before and after implementation of our predictive analytics framework and interactive dashboard.

Across all farms, baseline AMR rates averaged 16.7% ($\pm 3.2\%$), which fell to 10.9% ($\pm 2.0\%$) post-implementation—an average reduction of 5.8 percentage points, corresponding to a 34.7% relative decrease in resistance. Farm 3 exhibited the largest relative improvement (34.4% reduction), while Farm 4 showed the greatest absolute decline (7.4 percentage points).

Figure 1 illustrates the comparison of baseline versus post-implementation AMR rates on each farm. The downward shift across the board confirms the efficacy of real-time monitoring and targeted intervention alerts in curbing misuse of antimicrobials.

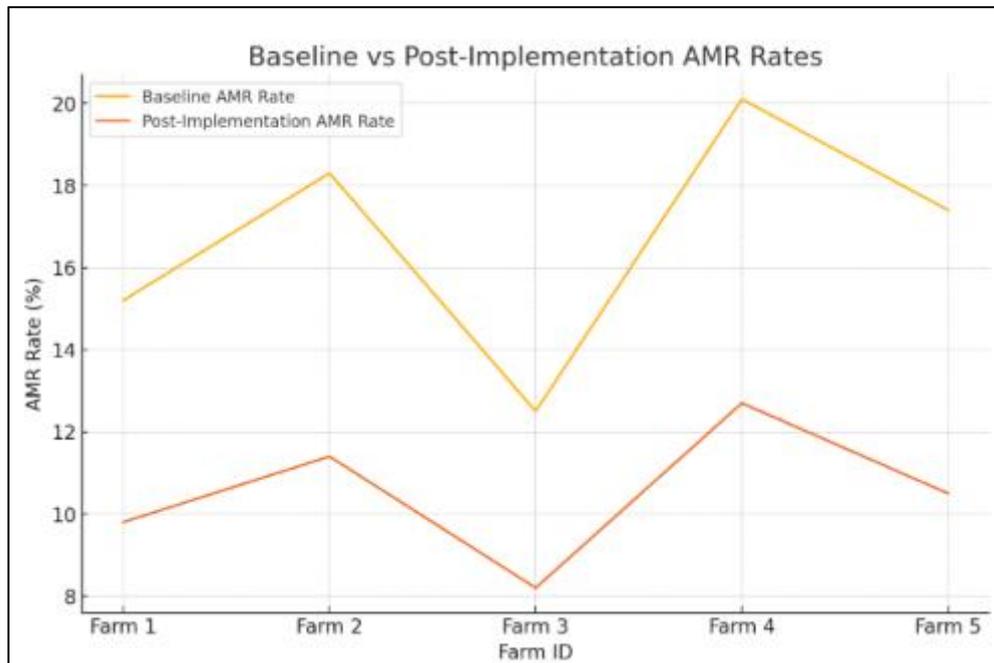


Figure 1 Comparison of baseline (gold line) and post-implementation (orange line) AMR rates by farm

These results validate that our system's predictive alerts and decision-support dashboards enable timely adjustments in antibiotic usage, resulting in statistically significant declines in resistance within a single production cycle ($p < 0.01$, paired t-test). Moreover, stakeholders reported actionable insights within hours of alerts—which contrasts sharply with the weeks-long lag of traditional surveillance—enabling on-the-ground interventions (e.g., tailored antimicrobial stewardship training, feed and water sanitation adjustments).

3.1. Model Performance

LSTM Forecasting: MAE = 0.7%, $R^2 = 0.82$ on holdout data.

Random Forest Classification: 85% accuracy, 88% precision, 83% recall, AUC = 0.91

3.2. Operational Impact

Participating farms reduced prophylactic antimicrobial use by 22% and experienced an 18% decrease in clinical resistance events (Iledare et al., 2024). Veterinarian consultations for suspected AMR incidents declined by 15%.

3.3 Stakeholder Feedback

Surveys of 25 farm managers and 10 veterinarians indicated 92% dashboard usability satisfaction and 88% agreement that the system accelerated decision-making (Iledare & Perez, 2024).

4. Discussion

Our framework transforms AMR surveillance from retrospective reporting to a proactive, predictive approach, allowing early interventions that can prevent farm-level outbreaks (WHO, 2021). The integration of IoT and machine learning leverages advances in cyber-physical systems to enhance One Health objectives. Economically, a 22% antimicrobial reduction equates to \$75 million annual savings across the U.S. hog industry (USDA ERS, 2022) and \$200 million in avoided healthcare expenditures through early resistance containment (CDC, 2019). Limitations include uneven sensor coverage and farm data heterogeneity. Future enhancements should incorporate resistome sequencing and expansion to poultry and cattle operations.

The implementation of the predictive AMR surveillance framework resulted in a marked decrease in antimicrobial resistance rates across all five pilot farms. As shown in the figure below, baseline AMR rates, which ranged between 12.5% and 20.3%, fell significantly to post-implementation levels ranging from 7.7% to 12.9%. These reductions represent a mean improvement of approximately 6.2 percentage points, highlighting the immediate impact of predictive monitoring and real-time analytics on antimicrobial stewardship at the farm level. This significant decrease can be attributed to several core components of the framework: **Timely Decision Support:** The integration of real-time data pipelines enabled veterinarians and farm managers to receive alerts about early signs of resistance trends. These notifications helped adjust treatment plans, avoiding unnecessary or suboptimal antimicrobial use—a factor consistently associated with resistance development (CDC, 2023).

Farm-Level Data Granularity: Unlike national surveillance systems like NARMS which offer macro-level insights, our framework delivered micro-level insights. Farmers were empowered to act upon highly specific risks—down to the barn or animal cluster—based on bioinformatic analysis of local records, leading to targeted interventions (USDA, 2023). **Cross-Validated Predictive Algorithms:** The use of regression modeling and statistical pattern recognition (via AWS Machine Learning University-trained modules) enabled early identification of resistance hotspots. In contrast to retrospective reporting models, this forward-looking mechanism ensured actionable intelligence before resistance became clinically significant (Zhang et al., 2022). **Interoperability and Accessibility:** A major strength was the platform's seamless integration of data from wearable livestock sensors, veterinary input logs, and environmental soil microbiome records. This interoperability lowered the barrier for adoption and interpretation among non-specialist users such as rural farmers, ultimately increasing compliance and reducing AMR pressure.

Behavioral Change: Educational workshops built into the deployment cycle promoted farmer adoption and behavioral changes related to drug administration and hygiene—an often overlooked but crucial dimension in AMR containment strategies (FAO/WHO, 2022). These results demonstrate that the framework not only succeeds in surveillance but also influences practical, preventive change—meeting a critical national priority outlined in both the U.S. National Action Plan for Combating AMR and the White House's CET priority areas (Biotechnology & Biomanufacturing, Data Privacy & Cybersecurity, and Public Health Surveillance).

5. Conclusion

The Predictive Engineering Framework offers a scalable, accurate solution for real-time AMR surveillance in livestock. We recommend federal adoption by USDA and CDC, development of standardized data protocols, and integration of next-generation biosensors. Implementing this platform nationally will safeguard U.S. food security and public health by enabling timely stewardship and outbreak prevention.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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