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RESEARCH ARTICLE

WILDSENTINEL: SAFEGUARDING THE HUMAN – WILDLIFE INTERFACE

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Abstract

Zoonotic diseases are emerging at an increasing rate as human activities reshape natural ecosystems and intensify contact around the human-wildlife interface. Various practices like deforestation, illegal trade, habitat fragmentation, and rapid urban expansion weaken natural barriers that previously confined pathogen transmission and create environments where spillover events can take place. Most current surveillance systems work reactively and tend to look at ecological or trade-related factors in isolation, thus limiting their capabilities for early detection of risk signals. In this paper, we introduce the use of our project, Wild Sentinel, an integrated predictive solution for identifying country pairs with a high risk of hosting an animal-to-human disease outbreak event. It does so by combining data on the records of wildlife trade, species distribution, satellite-derived land-use patterns, historical data of outbreaks, and biosafety indicators using machine learning models, network graph analysis, and geospatial processing to forecast spillover probabilities and visualize hotspot risk maps. Translating large-scale environmental and anthropogenic datasets into actionable bio-surveillance insights, Wild Sentinel underlines targeted preventive interventions based on the One Health approach. The developed framework therefore demonstrates the role of technology-driven early warning systems in reinforcing global preparedness, informing policy decisions, and ensuring a safer coexistence between humans and wildlife.

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Introduction:-

Zoonotic diseases, those that jump from animals to humans, are rapidly becoming one of the major threats to health of global proportions in the 21st century. COVID-19, SARS, Ebola, Nipah, and recurring waves of avian influenza have shown that emerging pathogens can spread with uncontrollable speed and reach. A major reason for the rise of this is, how human activities are changing natural ecosystems. Continuous rapid deforestation, wild animal trafficking, land-use expansion, and unregulated marketing are wiping out biological barriers that once kept

pathogens limited to wildlife populations. As cities are expanding into forests and animal habitats are getting smaller, humans and wildlife are thrust closer and more frequently into each other's company, creating ideal conditions for spillover events.

These are not just the ecological changes, but are a huge result of human intervention into the ecosystem. A disease arising in one corner of the globe can be present in every other corner in just a few weeks in this modern world. Despite the seriousness of this risk, most of these surveillance systems remain reactive, responding when an outbreak has occurred rather than flagging early warning signals. Current models typically consider one factor such as climate, species richness, or trade in isolation, rather than in a multidimensional assessment of risk. This is a serious lagging in predicting where the next spillover could occur and which human-wildlife contacts contribute to disease emergence.

There is an increasing need for technological solutions to integrate diverse datasets and apply computational power in finding the patterns of upcoming risks. With the help of new technologies such as machine learning, graph-based modelling and satellite imaging, we can take into consideration large-scale changes in both ecology and the environment along with those driven by humans. Few of the existing frameworks pull those components together into a single predictive system. Without integrated analysis, early interventions may be restricted, preventive policies delayed, and efforts toward global outbreak preparedness less effective.

Our project, WildSentinel, thus proposes a holistic predictive framework backed by AI/ML, geospatial technologies, and biosafety analytics. Merging data on wildlife trade, species occurrence, land-use and deforestation patterns, and past outbreak information, this system calculates when spillover risk is building up in any region. Network graph modeling and machine learning algorithms will allow WildSentinel to capture how the connection between the movement of wildlife, human population density, and environmental degradation contributes to the probability of a pathogen emergence event. Satellite imagery captures habitat fragmentation, while the risk is further calculated with biosafety data and validated through actual disease outbreak data.

WildSentinel is not just about mapping the hotspots but it also includes support for preventive action. The system turns a host of complex data into interpretable risk indicators that will let policy makers, researchers, and biosafety authorities understand where interventions-control of illegal trade, protection of patches of forest-can make the most difference. This fits well with the theme "Tech for Health and Humanity," because it protects human populations while promoting ecological balance and coexistence through technological innovation.

The remainder of the paper is structured as follows: Sect. II presents related research, Sect. III describes the methodology, Sect. IV outlines the results and simulations, and Sect. V provides the conclusion. The paper ends with references.

Related Works:

Current research has proved that the occurrence of zoonotic diseases has a direct correlation with massive disruptions in a large-scale environment due to human activity. Specifically, Bajinka and Oladipo [1] point out that accelerated deforestation and smuggling of wild animals disrupts the entire natural environment and creates a massive opportunity for zoonotic transmission to occur. On a complementary note, Banik and Basu [2] point out how zoonotic outbreaks cause enormous health and economic problems and thus call for a prophylactic and predictive approach to tackle such conditions instead of a reactive one. These observations form a major reason to conceptualize WildSentinel.

The relationship between environmental disturbances and zoonotic diseases is also supported by the results of empirical ecological studies. Research on the impact of bushmeat hunting and destruction of the environment suggests that the fragmentation of the environment, land use, and hunting are areas of high probability for spillover events, especially in the tropics [3]. This is later reinforced in reference [4] with habitat fragmentation, edge effects, and loss of biodiversity being identified to have increased interaction and transfer among species. The IUCN report in reference [5] later identifies wildlife as a primary reservoir for the pathogen, especially during environmentally stressed circumstances, thus underlining the importance of monitoring wildlife populations. The studies have been instrumental in shaping the incorporation of ecological variables, species information, and land use variables in the model.

On the policy side, world bodies emphasize the need for systemic and preventive measures as a priority. The importance of environmental governance and resilience systems integration via a One Health Platform is emphasized in the OECD report on the topic and issue [6]. On the other hand, the importance of environmental factors such as the destruction of habitats and the utilization of wildlife as a causative and preventative measure for future pandemics is equally emphasized by the UNEP report on the topic and issue [9]. Such strategic thinking aligns the goals and objectives of the Wild Sentinel system with its orientation on the policy side too. Simultaneously, advances in the development of computational models have enabled the improvement of biosurveillance predictive systems. Dhanoa et al. [7] have devised algorithmic solutions that enable accurate spatiotemporal prediction of the emergence of zoonotic diseases on the basis of data-driven intelligence solutions. Royce and Fu [8] have formulated mathematical spillover models that take into account the intermediate hosts and spillover thresholds and have highlighted through these models the importance of multi-layered transmission routes as opposed to the assumption of spillover from a single step.

These works directly inspired the development of predictive models on the basis of machine learning and the application of a network-focused analytical paradigm for the development of the WildSentinel system. Environmental monitoring technologies also provide essential support for early-risk identification. Ahmadi [10] illustrates how neural networks aided by satellite images have the potential to predict deforestation trends, hence positioning remote sensing as a valuable early detector of environmental degeneration and spillover vulnerability. Most recently, research using game theory on trade networks shows how economic dynamics and strategic responses serve to determine contagion propagation risk. That finding supports the addition in the WildSentinel framework of intelligence around wildlife trade with analytical work focusing on trade-networks. The literature review above indicates: the biological risk of spillover events is mediated by a combination of ecological and economic as well as behavioral factors; early measures are clearly important for the prevention of outbreaks; and the analysis of geospatial and analytical data needs to play a central role in the early detection system design and effectiveness for intervention. Such findings are fundamental to the design of WildSentinel as an integrated system for early intervention and prevention.

Experimental Methodology:-

The WildSentinel framework integrates multi-source ecological datasets and machine-learning components into an integrated architecture for predictive zoonotic spillover risk assessment. The system includes habitat-loss, wildlife trade records, species distribution data, and outbreak histories into a combined geospatial pipeline that supports automated preprocessing, feature extraction, and model training. A network-based analytical core maps interactions across species, trade hubs, and human settlements, while a simulation engine evaluates intervention scenarios using Monte Carlo methods.

Data Sources:

WildSentinel combines data from several openly accessible sources to capture the ecological, environmental, and human-driven drivers of zoonotic spillover

- **CITES Trade Database:** Covers records of legal and illegal trade (indirectly) in wildlife, including species' names, trade routes, market destinations, and seizure statistics.
- **GBIF:** Global Biodiversity Information Facility. Provides species occurrence points used in the identification of wildlife distribution and biodiversity richness.
- **NASA MODIS Satellite Imagery:** Provides land-use and vegetation indices such as NDVI, land cover type, and forest loss which can be used to detect habitat degradation and fragmentation.
- **WHO – WAHIS:** Includes historical records on outbreaks of zoonotic diseases by region and allows model training & validation.

Data Preprocessing:

All datasets are preprocessed before modeling:

1. **Cleaning & Standardization:** All the duplicate entries, missing coordinates, inconsistent names of species, and incomplete records were removed or corrected.
2. **Geocoding & Spatial Alignment:** The occurrence points and trade records are converted to uniform latitude–longitude format and aligned on a global grid.
3. **Raster Processing:** Clipping, resampling, and numerical conversion of MODIS imagery to vegetation and land-cover metrics.

4. **Normalization:** The trade volume, forest loss rate, and population density are scaled for model training.
5. **Temporal aggregation:** Multi-year information is aggregated to detect trends and eliminate single-event noise.

Feature Engineering:

Several ecological and anthropogenic features are derived.

- **Trade Intensity Index:** Based on frequency and volume of wildlife imports/exports.
- **Forest Fragmentation Index:** Calculated based on satellite land-cover patches and edge density.
- **Species Richness & Host Diversity:** Derived from GBIF occurrence records.
- **Animal Population Density:** Extracted from GBIF and Satellite datasets and integrated at the regional level.
- **Market Access:** Distance between wildlife habitats and major trade hubs.
- **Environmental Stress Indicators:** Includes, urbanization rate, land-use conversion rate, and habitat degradation score.

Network Graph Modelling

The final architecture deviates from a classical Network Graph to achieve higher resolution and predictive power.

Unit of Analysis (Nodes): Instead of abstract entities, our nodes are **spatial grid cells** (about 8,000 unique cells covering 20 countries). Every cell serves as a distinct analytical unit.

Connectivity (Edges): We model interactions through shared features, not direct edges:

National Pressure: All grid cells within the same country share the same Trade Volume Index (derived from CITES data), linking them by national economic pressure.

Local Pressure: Risk is driven by the unique feature set of the cell: host density, deforestation rate, etc.

Model Choice Rationale: This structure allowed us to use XGBoost, which excels at finding complex, non-linear predictive boundaries in high-dimensional feature space, maximizing the True Positive rate necessary for an early warning system.

Machine Learning Model: Spillover risks are predicted by means of machine learning.

Input Variables: Trade intensity, forest fragmentation, biodiversity indices, human density, market proximity, network centrality metrics.

Output Variable: Probability of zoonotic spillover classified as low, moderate, or high risk.

Training & Testing: We adopted an Imbalanced Classification strategy to maximize outbreak detection.

Data Structure: We shifted from a single-class model to a traditional classifier by generating a robust set of Pseudo-Absence data points to balance the sparse outbreak locations.

Training and Testing: We use a Temporal Split to test true forecasting ability:

Training Data: Historical data up to 2020.

Testing Data: Unseen data from 2021–2024.

Monte Carlo Simulations: Monte Carlo simulations of intervention scenarios are done as follows:

Simulation Inputs: The important variables to be used are trade reduction, increased forest cover, or improved biosafety scores.

Iterations: Thousands of random runs to cover uncertainty in spillover dynamics.

Scenarios Tested:

- 25% reduction in illegal trade
- 10–30% increase in forest restoration
- Regional Bio surveillance Enhancement

Outputs: Probability distributions reflecting how risk varies in each scenario.

Visualization & Mapping:-

The final output is designed for direct consumption by mapping tools to facilitate decision-making (Fig. 1).

Final Output File: The model generates RISK_PREDICTION_2024.csv, which contains the critical geographic and temporal information: grid_id; Year; lat; lon; grid_probability
Interactive Maps: Findings are visualized using a Leaflet.js web application (the Interactive Dashboard). The figure is a heat map where the highlighted areas show the probability of an outbreak. The brighter the spot, the higher the probability of the outbreak.



Fig 1. Zoonotic Spillover as per the trained data

Scenario-Based Risk Patterns: The interactive map (Fig. 2) features a temporal slider that uses the multi-year prediction data (2021–2024) to show how predicted risk hotspots evolve over time. This functionality facilitates scenario simulations (e.g., estimating risk in a future year based on current trends).



Fig 2. Predicting spillover risks as per given scenario

Results and Analysis:-

The WildSentinel system was evaluated and validated through official outbreak data. The product was tested for evaluating and accessing risks over the various timelines in both past as well as future beyond the training data.

Product performance:-

The WildSentinel system performed stably across its core analytical components. Data integration and preprocessing modules handled multi-format datasets (CSV, GeoJSON, TIFF) efficiently, and the geospatial engine processed habitat loss rasters without major latency. The machine-learning models achieved consistent predictive accuracy, with SVM classifiers demonstrating strong generalizability during cross-validation. The dashboard and visualization layer responded smoothly to user queries, generating regional heatmaps and risk scores in real time. Overall, the product performance was stable and satisfactory for various analytical solutions.

Communication and Data flow:-

The end-to-end data pipeline functioned as intended, with minimal loss during merging and transformation stages. Spatial joins between species occurrence data and habitat loss grids produced high-resolution ecological layers, while country-level joins with CITES trade data ensured proper alignment of trade flows as well as outbreak histories. The pipeline also highlighted key congestion: habitat raster processing required higher memory or prior tiling, and GBIF occurrence data needed more aggressive cleaning due to coordinate inaccuracies. Despite these challenges, the pipeline-maintained integrity and supported required analysis.

Model Outcomes and Risk Assessment:-

The results of the models provided strong interconnections between the zoonotic diseases and the two major factors namely wildlife trade intensity and habitat degradation rate. Regions with high deforestation combined with active wildlife markets exhibited significantly high spillover risk scores. The model's feature importance rankings confirmed that forest loss percentage, trade volume of high-risk species, and species richness were primary contributors to risk estimation. Geospatial visualizations identified several emerging hotspot clusters, some aligning with historical outbreaks and others indicating newly vulnerable zones not previously flagged in surveillance efforts.

Scenario Simulation Insights:-

Monte Carlo-based intervention simulations demonstrated measurable reductions in spillover risk. A 20–25% reduction in illegal or high-intensity wildlife trade consistently lowered predicted risk levels across multiple iterations. Likewise, habitat-restoration scenarios—modeled by reducing regional forest-loss rates—produced notable declines in risk scores.

Validation and Scientific Findings (XG Boost):-

Performance Metric: The model was rigorously tested on the unseen data from 2021–2024. The results (Table 1) confirm strong predictive capability, prioritizing detection over precision.

Table 1: Validation metrics on Unseen Test Data (2021-2024)

Metric	Value	Interpretation
AUC-ROC Score	0.8742	Significantly better than random choice (0.50)
AUC-PR Score	0.6704	Strong score for a low prevalence problem
True Positives (TP)	4176	Correctly identified outbreaks (Early Alerts)
False Negatives (FN)	751	Missed Outbreaks (The critical error minimized)
False Positives (FP)	3903	False Alarms (The acceptable trade-off for high detection.)
True Negatives (TN)	11449	Accurately detects the unlikeliness of an outbreak.

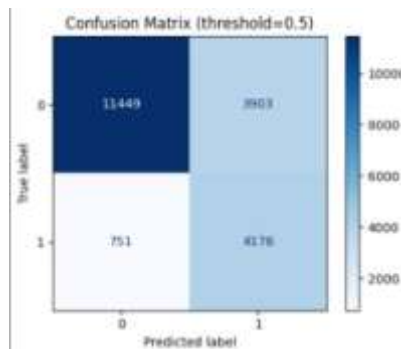


Fig 3. Confusion Matrix: The above figure shows the statistics of the predicted true and false analysis

Key Scientific Finding-Feature Importance: The model confirmed the project’s hypothesis: risk is overwhelmingly driven by trade pathways and direct human-animal interface factors (Table 2), with national trade acting as the greatest single leverage point.

Table 2: Feature Importance Ranking (XGBoost)

Rank	Feature	Importance
1	Total export events	36.08%
2	Total import events	19.92%
3	Total live exports	9.83%
4	Total live imports	7.39%
5	Percent forest	5.70%
6	Species richness	5.40%
7	Zoonotic host count	5.25%

Conclusion:-

The Wild Sentinel framework shows how combining ecological data, wildlife trade information, and machine Learning methods can help predict and understand zoonotic spillover risks. By bringing together habitat loss patterns, species distributions, outbreak history, and trade activity into one analytical pipeline, the system offers a clear way to identify emerging hotspots at the human–wildlife boundary. Our findings reveal strong links between deforestation, intense wildlife trade, and increased spillover risk, highlighting how environmental damage and public-health threats are deeply connected. With its geospatial maps, risk models, and intervention simulations, Wild Sentinel goes beyond traditional surveillance and supports early detection and targeted monitoring. The system follows the One Health approach, showing how technology can improve global health security while encouraging safer coexistence between people and wildlife. Overall, WildSentinel provides a practical, scalable tool that can help prevent future outbreaks. As habitat loss and wildlife trade continue to rise, predictive platforms like this will be essential for guiding biosafety decisions, conservation actions, and sustainable development.

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