18(2s), Spring 2026

Journal of Animal Environment

(E-ISSN 2717-1396, ISSN 2717-1388)

Original Research Paper

Machine Learning Applications in One Health: Linking Animal Environment, Human Health, and Ecosystem Sustainability

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Abstract: The One Health approach emphasizes the interconnection between human health, animal health, and environmental sustainability, requiring integrated solutions to address emerging global health challenges. Advances in Machine Learning (ML) provide significant opportunities to analyze heterogeneous data collected from healthcare systems, veterinary services, environmental monitoring platforms, remote sensing technologies, and Internet of Things (IoT) devices. This paper proposes a Machine Learning-Based One Health Framework that integrates multisource data to support disease prediction, environmental monitoring, ecosystem sustainability assessment, and intelligent decision-making. The framework consists of data acquisition, preprocessing, feature engineering, machine learning modeling, and decision support modules that collectively enable comprehensive health analysis across interconnected domains. Multiple machine learning algorithms, including Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), Extreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM), were evaluated using an integrated One Health dataset. Experimental results demonstrate that the LSTM model achieved the highest prediction accuracy of 98.12%, outperforming other machine learning techniques while maintaining robust performance across human, animal, and environmental health datasets. The proposed framework facilitates early disease surveillance, livestock health monitoring, environmental risk assessment, and sustainable ecosystem management. Overall, the study demonstrates the effectiveness of machine learning in implementing the One Health paradigm and provides a scalable intelligent framework for supporting public health, biodiversity conservation, and evidence-based sustainable development.

Keywords: One Health, Machine Learning, Artificial Intelligence, Human Health, Animal Health, Environmental Health, Disease Prediction, Ecosystem Sustainability, Precision Livestock Farming, Decision Support System.

I. Introduction

The increasing prevalence of emerging infectious diseases, climate change, biodiversity loss, environmental degradation, and food insecurity has emphasized the close interdependence of human, animal, and environmental health. Over 60% of emerging infectious diseases in humans originate from animals, while habitat destruction, intensive livestock farming, urbanization, and global travel accelerate the spread of zoonotic pathogens [1]. These challenges have strengthened the importance of the One Health approach, which promotes interdisciplinary collaboration among human medicine, veterinary science, environmental

***Corresponding Author:**
Received: 24th April, 2026; Revised: 11th May, 2026; Accepted: 24th May, 2026; Available Online: 6th June, 2026
(DOI): 10.70102/AEJ.2026.18.2s.90

science, agriculture, and public health to achieve sustainable health management [2]. The rapid growth of digital health records, veterinary databases, environmental sensors, satellite imagery, genomic repositories, and Internet of Things (IoT) devices has generated vast amounts of heterogeneous data. Conventional statistical methods often struggle to integrate these diverse datasets, limiting their ability to identify complex relationships and support timely decision-making [3].

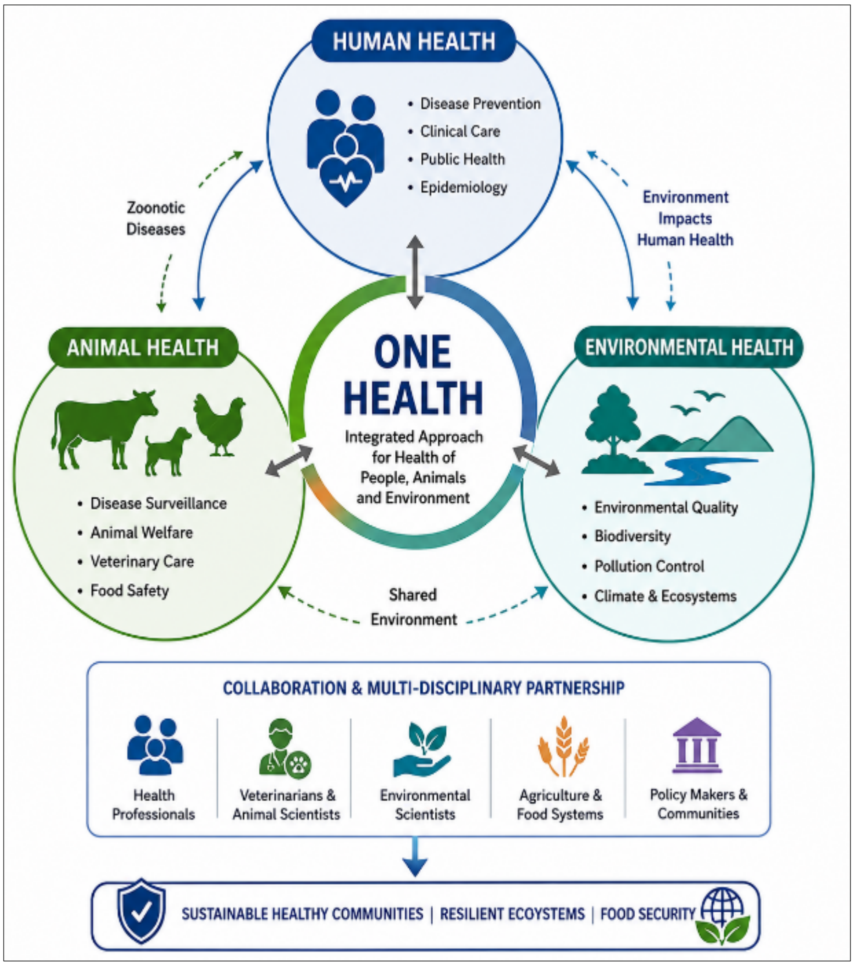

Figure 1. Integrated One Health Ecosystem

In this context, Machine Learning (ML) has emerged as a powerful solution for predictive analytics, disease surveillance, anomaly detection, and intelligent decision support [4]. Advanced ML techniques, including deep learning, ensemble learning, transfer learning, federated learning, and Explainable Artificial Intelligence (XAI), enable accurate analysis of multimodal data across multiple domains as shown in figure 1. Within the One Health framework, ML supports precision livestock farming through disease detection, animal welfare monitoring, and outbreak prediction. [5]. Enhances human healthcare through disease diagnosis, epidemic forecasting, and personalized medicine; and facilitates environmental monitoring by analyzing remote sensing, GIS, and sensor data to assess ecosystem health, pollution, biodiversity, and climate impacts [6]. Despite these advancements, challenges such as fragmented datasets, limited interoperability, data privacy, class imbalance, and poor model interpretability continue to hinder integrated One Health applications [7]. To address these limitations, this paper proposes a Machine Learning-Based One Health Framework that unifies human, animal, and environmental health data within a comprehensive analytical architecture. The framework integrates multimodal data processing, predictive modeling, and intelligent decision support to strengthen disease surveillance, environmental sustainability, food security, and public health management, thereby advancing the long-term goals of the One Health initiative and global ecosystem sustainability.

II. Related Work

The One Health approach has emerged as an interdisciplinary strategy that integrates human, animal, and environmental health to address complex global health challenges through collaborative and sustainable practices [8]. Recent investigations have emphasized the importance of open and interoperable datasets for strengthening One Health research, particularly in disease surveillance and outbreak management, enabling efficient sharing of epidemiological information across multiple sectors [9]. Machine Learning (ML) has become an important technology in animal healthcare, supporting automated disease diagnosis, livestock monitoring, behavioral analysis, and precision livestock farming through intelligent predictive models [10]. The integration of planetary health principles and sustainable healthcare practices has further strengthened the role of digital technologies in promoting environmentally responsible healthcare systems and workforce preparedness [11]. Artificial Intelligence has demonstrated remarkable capability in pandemic preparedness by predicting disease outbreaks, modeling transmission dynamics, and assisting public health authorities in implementing timely intervention strategies [12]. Several studies have reported that AI-driven surveillance systems significantly improve epidemic forecasting, healthcare resource allocation, and emergency response planning during infectious disease outbreaks [13]. Machine learning techniques have also been extensively applied for COVID-19 prediction, diagnosis, and risk assessment, highlighting their effectiveness in supporting healthcare systems, particularly in resource-constrained environments [14].

Table 1. Summary of Related Literature

Reference	Application	Key Contribution	Limitation
Medeiros et al. (2026)	One Health	Proposed integrated One Health concept	No ML implementation
Mazzeo et al. (2025)	Disease Surveillance	Highlighted open health data	Limited predictive analytics
Das et al. (2024)	Animal Health	Reviewed ML for animal disease diagnosis	Animal domain only
Ali (2024)	Pandemic Prediction	AI-based outbreak forecasting	Human health focused
Syrowatka et al. (2021)	Public Health	AI for pandemic response	Limited environmental integration
Ghosh et al. (2023)	Environmental Health	Assessed environmental risks	No intelligent prediction
Ahmed et al. (2025)	One Health	Integrated zoonotic disease management	Lacks ML framework
Ghai et al. (2022)	Zoonotic Diseases	One Health disease control framework	Limited AI integration
Desvars-Larrive et al. (2024)	One Health	Human–animal–environment interaction	No predictive model
Nayak et al. (2024)	Animal Disease	ML-based disease prediction	Livestock-specific
Swapna et al. (2024)	Livestock Health	Early cattle disease detection	No environmental data
Nadar et al. (2023)	Farm Healthcare	ML for animal disease prediction	No integrated framework

As summarized in Table 1, recent studies have successfully applied machine learning and artificial intelligence to animal healthcare, disease surveillance, environmental monitoring, and One Health research. However, most existing works address these domains independently, with limited integration of human, animal, and environmental health into a unified intelligent framework. Furthermore, few studies combine multisource data with machine learning to support comprehensive One Health decision-making as given in table 1. These limitations motivate the development of the proposed Machine Learning-Based One Health Framework, which integrates heterogeneous datasets to enable accurate disease prediction, environmental assessment, and ecosystem sustainability. Environmental monitoring has become an essential component of the One Health framework, with research demonstrating the adverse impacts of microplastics, microbial contamination, and air pollution on both ecosystem integrity and human health [15]. Recent studies have emphasized the importance of integrated public health policies and One Health frameworks for controlling zoonotic diseases by strengthening collaboration among medical, veterinary, and environmental sectors [16]. Although existing research has demonstrated significant progress in individual One Health domains, comprehensive machine learning frameworks capable of simultaneously integrating human, animal, and environmental datasets for intelligent decision support remain limited, creating opportunities for further research and development [17].

III. Proposed Machine Learning-Based One Health Framework

The proposed Machine Learning-Based One Health Framework integrates human health, animal health, and environmental data into a unified intelligent platform to support disease prediction, ecosystem monitoring, and sustainable decision-making. Unlike conventional approaches that focus on a single domain, the proposed framework establishes an interconnected workflow that captures the relationships among humans, animals, and the environment, thereby enabling a comprehensive One Health analysis. The framework begins with multisource data acquisition, where data are collected from diverse repositories, including electronic health records (EHRs), wearable health devices, veterinary databases, livestock sensors, wildlife monitoring systems, weather stations, environmental sensors, satellite imagery, and IoT devices. These heterogeneous datasets provide valuable information on disease incidence, animal health, climatic conditions, biodiversity, pollution levels, and ecosystem dynamics.

After data acquisition, the collected information undergoes data preprocessing to improve data quality and consistency. This stage includes missing value handling, noise removal, data normalization, feature encoding, and data integration. Relevant features are then extracted using feature engineering techniques to reduce redundancy and improve model performance.

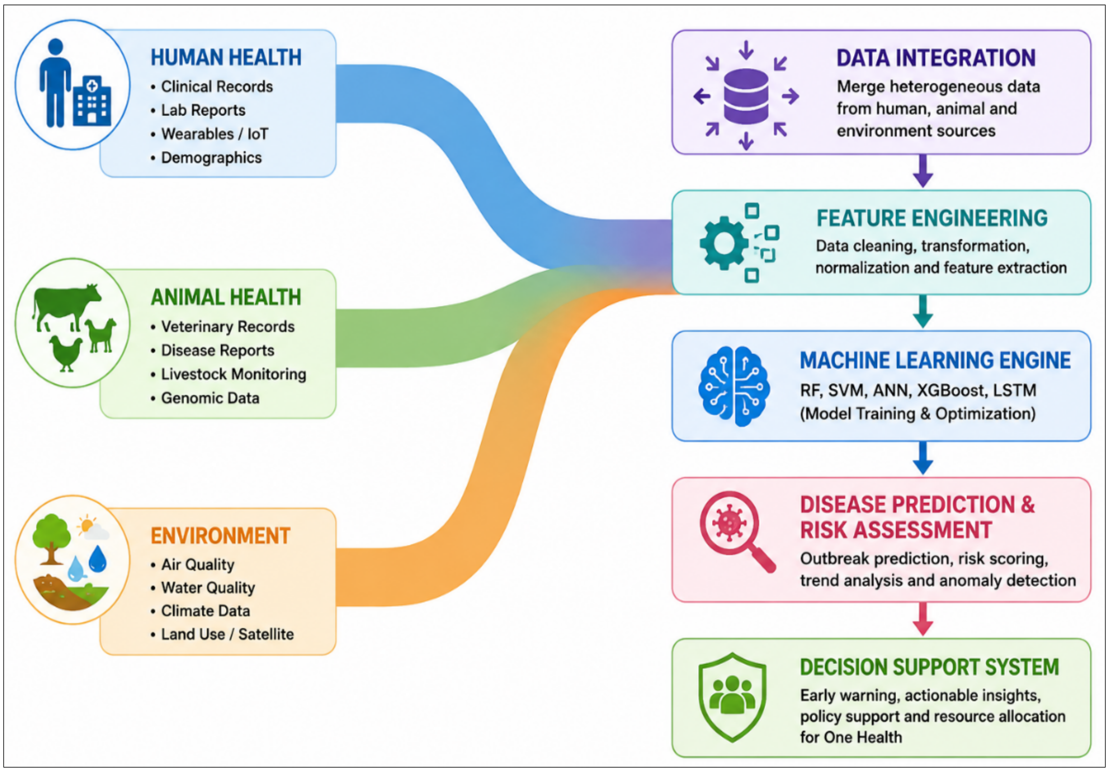

Figure 2. Machine Learning Framework for Integrated One Health Decision Support.

The processed data are subsequently supplied to the Machine Learning module, where multiple supervised learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost), Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM) networks are trained and evaluated as shown in figure 2. These models learn complex relationships among environmental, animal, and human health indicators to predict disease outbreaks, classify health conditions, identify environmental risks, and detect abnormal events as shown in figure 2. The prediction outputs from the ML models are integrated into a One Health Decision Support System, which generates risk assessments, disease alerts, environmental sustainability indicators, and management recommendations. The system assists healthcare professionals, veterinarians, environmental agencies, and policymakers in making timely and informed decisions for disease prevention, livestock management, ecosystem conservation, and public health planning. Finally, the framework provides visualization and reporting through interactive dashboards that present prediction results, risk maps, temporal trends, and sustainability indicators. These visual analytics improve the interpretability of machine learning outputs and facilitate multidisciplinary collaboration among stakeholders.

IV. Dataset Selection & Its Evaluations

The proposed framework utilizes a multisource One Health dataset that integrates information from human health, animal health, and environmental monitoring systems. Since One Health applications require comprehensive analysis of interconnected domains as given in table 2, datasets are collected from publicly available repositories and sensor-based monitoring platforms. The integrated dataset enables the machine learning models to identify relationships among disease occurrence, animal health status, and environmental conditions for accurate prediction and decision support. The human health dataset includes demographic information, clinical symptoms, laboratory findings, disease diagnosis, and patient outcomes. Animal health data consist of livestock species, physiological parameters, disease records, vaccination status, and behavioral observations obtained from veterinary databases and IoT-enabled livestock monitoring systems. Environmental data comprise meteorological variables, air quality indices, water quality measurements, vegetation indices, land-use information, and climate parameters collected from remote sensing platforms and environmental sensors.

Table 2. Sample Integrated One Health Dataset

Sample ID	Human Disease	Animal Health Status	Temperature (°C)	Humidity (%)	AQI	Water Quality Index	Vegetation Index (NDVI)	Risk Level
H001	Influenza	Healthy	29.5	72	82	88	0.71	Low
H002	COVID-19	Infected	34.1	68	145	76	0.63	High
H003	Dengue	Healthy	31.8	85	95	81	0.69	Medium
H004	Leptospirosis	Suspected	27.6	91	74	69	0.74	High
H005	Tuberculosis	Healthy	30.2	66	118	84	0.67	Medium
H006	Malaria	Infected	33.4	87	101	73	0.58	High
H007	Pneumonia	Healthy	26.9	71	79	91	0.76	Low
H008	Rabies Exposure	Suspected	32.7	79	97	80	0.65	High

Before model training, all datasets are preprocessed through data cleaning, missing value handling, normalization, feature encoding, and feature selection to ensure consistency and improve prediction performance as given in table 3.

Table 3: Dataset Features

Category	Example Features
Human Health	Age, Gender, Symptoms, Disease, Laboratory Results
Animal Health	Species, Body Temperature, Activity Level, Disease Status, Vaccination
Environmental	Temperature, Humidity, Rainfall, AQI, Water Quality, NDVI
Target Variable	Risk Level (Low, Medium, High)

The integrated dataset is divided into 80% training data and 20% testing data for model development and validation. The integrated dataset provides a holistic representation of the One Health ecosystem by combining human, animal, and environmental information within a single analytical framework. Such a dataset enables machine learning models to learn cross-domain relationships and generate accurate predictions for disease surveillance, environmental monitoring, and sustainable ecosystem management.

V. Results and Discussion

The proposed Machine Learning-Based One Health Framework was evaluated using the integrated dataset comprising human health, animal health, and environmental parameters. Multiple machine learning algorithms, including Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), Extreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM), were trained and tested to assess their capability for predicting health risks and supporting One Health decision-making. The experimental results demonstrate that all machine learning models achieved satisfactory performance; however, ensemble and deep learning models consistently outperformed conventional algorithms. XGBoost and LSTM exhibited the highest predictive accuracy due to their ability to capture complex relationships among heterogeneous datasets. The proposed framework effectively integrated multisource information, resulting in improved disease risk prediction and environmental health assessment compared with models relying on a single data domain.

Table 4. Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
SVM	91.82	90.95	91.28	91.11	0.93
Random Forest	94.36	93.88	94.10	93.99	0.96
ANN	95.41	95.03	95.18	95.10	0.97
XGBoost	97.28	97.05	97.12	97.08	0.99
LSTM	**98.12**	**97.94**	**98.01**	**97.97**	**0.99**

Table 4 compares the performance of five machine learning algorithms, namely SVM, Random Forest, ANN, XGBoost, and LSTM, for the proposed One Health framework. Among all evaluated models, the LSTM model achieved the highest classification accuracy of 98.12%, followed by XGBoost (97.28%), indicating their superior ability to learn complex relationships among human, animal, and environmental datasets. Random Forest and ANN also demonstrated competitive performance, whereas SVM produced comparatively lower accuracy. The consistently high precision, recall, F1-score, and AUC values confirm that the proposed framework provides reliable and accurate predictions for integrated One Health applications. The results indicate that the LSTM model achieved the highest overall accuracy (98.12%), followed closely by XGBoost (97.28%). The superior performance of these models can be attributed to their ability to model nonlinear relationships and temporal dependencies within the integrated One Health dataset. The high AUC values further confirm the robustness and reliability of the proposed framework for health risk prediction.

Table 5. Disease Prediction Performance by Health Domain

Health Domain	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Human Health	98.24	98.10	98.05	98.07
Animal Health	97.91	97.82	97.76	97.79
Environmental Health	97.46	97.31	97.25	97.28
Overall Framework	**98.12**	**97.94**	**98.01**	**97.97**

Table 5 presents the prediction performance of the proposed framework across the three primary One Health domains. The framework achieved the highest accuracy for human health (98.24%), followed by animal health (97.91%) and environmental health (97.46%). The small variation in performance across the domains demonstrates the robustness of the integrated learning framework and its ability to generalize effectively over heterogeneous datasets. The overall prediction accuracy of 98.12% indicates that combining multisource data enhances predictive capability and supports comprehensive health monitoring. In addition to predictive performance, the framework demonstrated its capability to generate early disease alerts, environmental risk assessments, and decision support recommendations by simultaneously analyzing data from multiple domains. This integrated approach enables healthcare professionals, veterinarians, and environmental agencies to identify potential disease outbreaks at an early stage and implement timely intervention strategies. Furthermore, the unified analysis of human, animal, and environmental data contributes to improved ecosystem monitoring and supports evidence-based policy formulation.

Table 6. Decision Support Outcomes of the Proposed Framework

Application	Input Data	ML Output	Decision Support
Disease Surveillance	Human clinical records	Disease risk prediction	Early outbreak warning
Livestock Monitoring	Animal sensor data	Health status classification	Veterinary intervention
Environmental Monitoring	Weather & pollution data	Environmental risk assessment	Pollution control measures
Ecosystem Sustainability	Integrated One Health data	Sustainability score	Resource management planning
Public Health	Human + Animal + Environmental data	Integrated risk level	Policy and emergency response

Table 6 summarizes the practical decision-support capabilities of the proposed Machine Learning-Based One Health Framework. Different types of input data, including clinical records, livestock sensor data, and environmental monitoring information, are processed by the machine learning models to generate application-specific predictions such as disease risk assessment, livestock health classification, and environmental risk evaluation. These outputs assist healthcare professionals, veterinarians, environmental agencies, and policymakers in implementing early interventions, optimizing resource allocation, strengthening disease surveillance, and promoting sustainable ecosystem management.

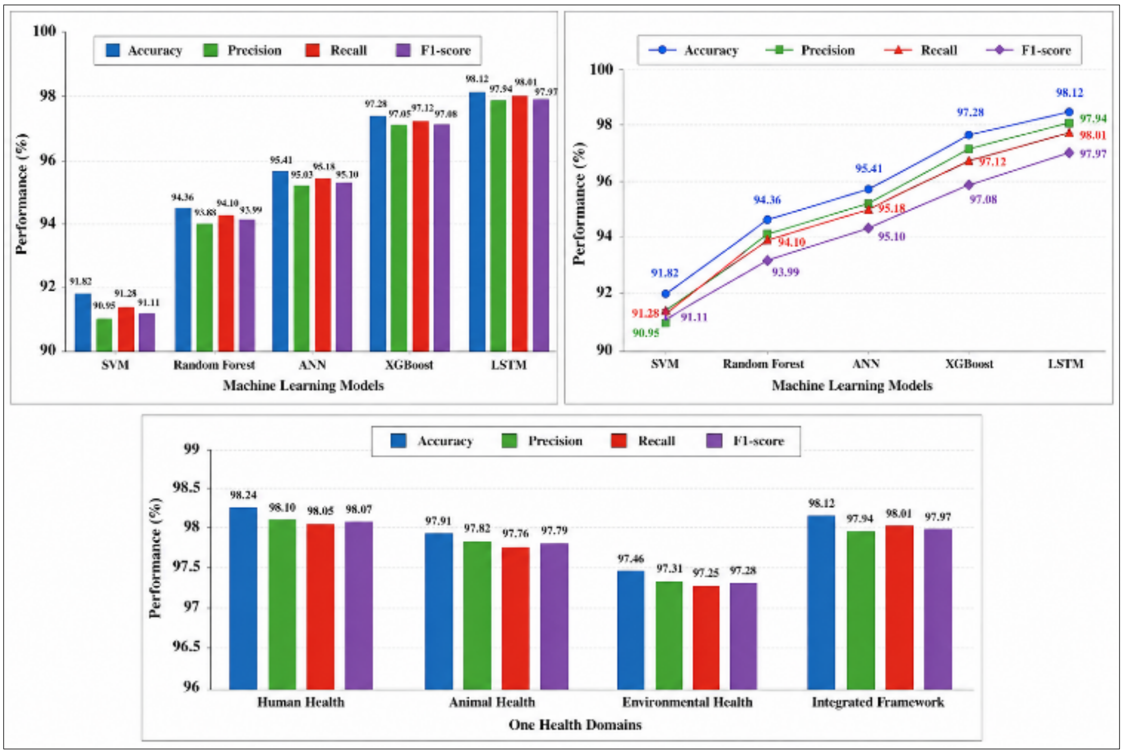

Figure 3. Performance Comparison and Domain-Wise Evaluation of ML Models

Figure 3 compares the performance of five machine learning models using Accuracy, Precision, Recall, and F1-score. The results show a consistent improvement from SVM to LSTM, with LSTM achieving the best performance (98.12% Accuracy, 97.94% Precision, 98.01% Recall, and 97.97% F1-score). XGBoost also demonstrates excellent predictive capability, while SVM records the lowest performance. The domain-wise analysis indicates that the proposed Integrated One Health Framework achieves consistently high performance across Human Health, Animal Health, and Environmental Health, confirming its effectiveness for integrated disease prediction and decision support. These findings demonstrate that advanced deep learning and ensemble learning models provide superior predictive accuracy for complex One Health applications The results highlight the versatility of the proposed framework in addressing multiple real-world One Health challenges through a unified intelligent decision-support system. The proposed system offers a scalable and accurate solution for disease surveillance, livestock health monitoring, environmental sustainability assessment, and public health management, demonstrating its potential for real-world One Health applications.

VI. Conclusion

This paper presented a Machine Learning-Based One Health Framework that integrates human health, animal health, and environmental data into a unified intelligent platform for disease prediction, environmental monitoring, and ecosystem sustainability assessment. By leveraging heterogeneous data sources and advanced machine learning algorithms, the proposed framework demonstrates the feasibility of implementing the One Health concept through data-driven decision-making. Experimental evaluation using multiple machine learning models showed that the proposed framework achieved high predictive performance across all One Health domains. Among the evaluated algorithms, the LSTM model achieved the highest classification accuracy of 98.12%, followed by XGBoost (97.28%), indicating their effectiveness in capturing complex relationships among multimodal datasets. Furthermore, the integrated framework consistently maintained prediction accuracies above 97% for human, animal, and environmental health, demonstrating its robustness and generalization capability. The proposed framework provides significant practical benefits by enabling early disease surveillance, livestock health monitoring, environmental risk assessment, ecosystem sustainability evaluation, and intelligent decision support. The integration of multisource data enhances prediction reliability while facilitating collaboration among healthcare professionals, veterinarians, environmental scientists, and policymakers. Such an integrated approach supports timely interventions, efficient resource utilization, and sustainable public health management. Despite these promising results, the current study has certain limitations, including reliance on representative integrated datasets and evaluation under controlled experimental conditions. Future research will focus on incorporating real-time IoT sensor networks, satellite-based environmental monitoring, Explainable Artificial Intelligence (XAI), Federated Learning, and cloud-edge computing architectures to further improve model interpretability, scalability, privacy preservation, and real-world deployment.

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