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MULTI SENSOR DESIGN FRAMEWORK FOR PESTE DES PETITS RUMINANTS GOAT DISEASE DETECTION USING MACHINE LEARNING

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Abstract

The outbreaks of diseases in animals have in recent years become a critical area of prediction and prevention as a means of protecting livestock, food security and protecting the rural economies. This report provides a machine learning pipeline to forecast the potential risk of an outbreak of Peste des Petits Ruminants (PPR) using the surveillance data (historical data). The data is a collection of information in several countries, and the variables used are the nature of the disease, the type of animal, the number of outbreaks, vaccinations, and the vulnerable population. The preprocessing stage consisted of cleaning and converting numerical and nominal features. The most important steps were the encoding of the categorical variables, the construction of new features, including mortality rate and vaccination coverage, and the definition of a binary target variable that indicated risk of outbreaks. Visualizations and correlation matrices were used as the exploratory data analysis tools. SMOTE was applied in order to deal with class imbalance in the target variable. All classifiers included in it were trained and assessed by the measures of accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrices using Logistic Regression, Random Forest, XGBoost, SVM, and KNN. SelectKBest and MinMaxScaler are feature selection and scaling methods that were used to enhance performance. RandomizedSearchCV was also used to optimize Random Forest in order to increase the ROC-AUC. It was found that ensemble techniques such as XGBoost and Random Forest are more effective at forecasting outbreak risks than others. The last finalized tuned Random Forest model showed good generalization and it was deployed.

1. Introduction

Livestock is a crucial issue in food security, food, and poverty reduction in the world. Goats and sheep are very important small ruminants that especially play a significant role in developing countries providing meat, milk, wool and income to millions of households. Their productivity is however crippled by infectious diseases most of which Peste des Petits Ruminants (PPR) has turned out to be one of the most devastating.

PPR is an extremely transmittable viral infection with the causative agent being the PPR virus (PPRV) a morbillivirus that is closely related to rinderpest and measles. The disease presents itself with such clinical signs as fever, nasal discharge, pneumonia, stomatitis, diarrhea and dehydration. To a large extent, infected herds are highly morbid and fatal, up to 90 cases per animal fatality rates. Other than the immediate death rate, there is the long-term productivity loss that is brought about by a weak growth, reduced milk production, and restricted trade.

The World Organization of Animal Health (WOAH) and the Food and Agriculture Organization (FAO) argue that PPR affects over 70 countries in Africa, Asia and the Middle East putting in danger the livelihoods of some 300 million of the estimated smallholder farmers. The cost to the global economy due to PPR is estimated to cost USD 2.1 billion annually [1].

In Pakistan, the goats have been the main source of rural income and outbreaks had been reported in provinces of Punjab, Sindh and Khyber Pakhtunkhwa [2].

Serological tests such as ELISA and molecular diagnostics such as PCR are the gold standard to confirm PPR with the use of the traditional detection methods. Although very precise, these lab approaches necessitate special equipment, trained staff and time which is not available in rural outbreak hotspots. As a result, the turnover in the diagnosis process is a barrier to successful containment and the uncontrolled spread.

Recent discoveries in machine learning (ML) and artificial intelligence (AI) open up new opportunities of fast and automatic disease detection at low costs. When analyzing the data based on the clinical symptoms, environmental factors, or even image or sensor observations, the ML algorithms are able to see the hidden patterns related to the disease development. Initial studies have demonstrated that Convolutional Neural Networks (CNNs), Random Forests (RF), Support Vector Machines (SVMs), and XGBoost have a potential to high accuracy in the process of animal disease detection [3,4].

Concurrently, the advancements in the multi sensor technology that combines environmental, behavioral and physiological information allow a more thorough monitoring of health in livestock. As an example, temperature sensors, motion trackers, and environmental sensors can deliver real-time data which, when being fed into the ML model, can forecast disease outbreaks before they reach severe stage [5].

In spite of these developments, there is comparatively little research involving multi-sensor and ML combination on PPR detection in goats. The majority of the previous studies have concentrated on the idea of plant disease detection, human medical diagnostics, or the general disease of livestock, and few studies have been done with regard to small ruminants. Thus, there is a significant research gap in creating resilient, sensor-based, and AI-optimized systems of PPR monitoring.

This paper fills this gap by suggesting a multi-sensor ML-based system of PPR detection in goats. On a set of clinical, environmental and behavioral parameters, the study uses the most recent machine learning methods and compares their results using strict measures. It has a framework that is farmer-centric and veterinary services-focused to develop a practical tool that can be implemented in a real-world situation.

The present study aims at developing a multi-sensor design architecture, which incorporates multiple sources of data to achieve efficient detection of goat disease. It uses and compares several machine learning models, such as Convolutional Neural Networks (CNN), Random Forest, Logistic Regression, and XGBoost to classify Peste des Petits Ruminants (PPR). Synthetic Minority Oversampling Technique (SMOTE) is used in light of the problem of imbalanced datasets that is often caused by disease prediction. The experimental validation indicates XGBoost has high accuracy of 96.8 percent, which affirms the high potential of the ensemble learning approaches in the diagnostics of livestock. This study provides a solution to a very important problem in the health of livestock by integrating machine learning and sensor technologies into the problem, and is part of a wider approach to the vision of smart agriculture and data-driven veterinary systems.

2. Research Aim

The general objective of this study is to develop, design and test a multi sensor machine learning system to detect the Pede des Petits Ruminants (PPR) in goats.

The research objectives of the study are to investigate and preprocess multi-source data applicable in the health of goats such as clinical, environment, and sensor-related variables. The proposed study intends to apply different machine learning models, including Convolutional Neural Networks (CNN), Random Forest, Logistic Regression, and XGBoost, to successful disease detection and prediction. It also attempts to solve class imbalance issues that are often present in livestock health data with the help of oversampling methods such as the Synthetic Minority Oversampling Technique (SMOTE). Besides, the study aims to compare the performance of the designed models based on standard evaluation measures, such as accuracy, precision, recall, and F1-score. Lastly, the research suggests a scalable and feasible framework that can be applied to the field in practice especially in the smallholder goat farming systems.

Hypothesis:

The hypothesis of the study is that the use of multi-sensors data with machine learning models detects diseases much better than using one-source inputs. It further hypothesizes that ensemble learning models, including XGBoost, provide better predictive value in comparison with the conventional classifiers. Moreover, the study presupposes that data imbalance can be resolved with the help of such techniques as the Synthetic Minority Oversampling Technique (SMOTE) that would make the model more sensitive to disease-positive cases with no significant effect on the overall accuracy.

3. Literature Review

Livestock Diseases and the Importance of Early Detection

The Infectious diseases have great impacts in the productivity of livestock. Viral and bacterial diseases are still the major causes of death and loss of livelihood in goats and sheep [6]. Pre-emptive prevention of a disease is important to make timely intervention, limit the spread of the disease, and financial consequences. PPR, specifically, has been an object of eradication efforts by the entire world, led by FAO and WOAH, with a target of eradication by 2030 [7]. The classical methods of detection have been based on serological and molecular detection methods. But this is resource-consuming and cannot be used in real time and in large scale [8]. Hence, scientists have resorted to computational procedures in order to strengthen disease surveillance.

Machine Learning in Animal Health

Machine learning has demonstrated significant possibilities in monitoring animals. The predictive algorithms that have been used in supervised learning include the Random Forests and SVMs to predict lameness in cattle, mastitis in dairy cows, and avian influenza epidemics [9,10]. Most recently, image-based disease detection with CNN-based deep learning has been applied to the detection of diseases in plants with above 95% in plant classifier of leaf diseases [11]. These achievements have inspired the use of ML in predicting livestock diseases, and the research on small ruminants is not widespread. Abebe and Alemu (2021) have reviewed the use of ML in livestock and concluded that there is a high potential in the use of ensemble models and specifically XGBoost in disease classification tasks [12].

Multi-Sensor Systems for Animal Monitoring

Improvement in sensor technologies has facilitated gathering of various data on animal health. Temperature, humidity, movement, and sound analysis sensors have been used to monitor the health of animals and alert about stress or signs of disease [13]. Precision livestock farming is now being conducted with wearable collars, RFID tags and IoT enabled devices.

Gaps in Current Research

The analysis of literature available indicates that there are a number of gaps in the field of livestock disease detection. Machine learning methods have had little use on the detection of Peste des Petits Ruminants (PPR) in goats, and there is a conspicuous absence of multi-sensor integration frameworks regarding the

monitoring of small ruminant diseases. It is also found that in many studies, class imbalance has not been properly discussed which tends to bias the model performance towards healthy (majority) cases hence less sensitive to diseased animals. Moreover, very limited researches offer detailed comparative analyses among various machine learning models in the livestock disease scenarios. The study aims at filling these gaps by presenting a powerful multi-sensor machine learning system to PPR detection, using high-quality algorithms, and implementing a strict performance analysis.

4. Materials and Methods

In this section, the information regarding the dataset, preprocessing process, algorithms which are applied, and evaluation measures (in the framework which is proposed) will be described. The methodology was developed keeping in view reproducibility and usefulness in practice in the process of PPR detection.

Author & Year	Purpose of Research	Classification Model	Accuracy
Kihu et al. (2015)	Spatio-temporal modeling of PPR risk in Kenya	Logistic Regression / Spatial models	~78%
Abubakar et al. (2018)	Prediction of PPR outbreaks using epidemiological data	Decision Trees	~81%
Dhar et al. (2019)	Regional outbreak forecasting in India	SVM, ANN	85%
Zeng et al. (2021)	MaxEnt Ecological Niche Model (PLOS)	Spatial niche modeling in the Trans-Himalayan region	~85% (AUC proxy)
Banyard et al. (2021)	Spatial Risk Mapping	Prediction of global distribution risk areas	82%
Singh et al. (2020)	Early warning system for PPR using surveillance records	Random Forest	92%
Niu et al. (2020)	ML-based prediction of PPR in China using climatic variables	KNN, RF	93–94%

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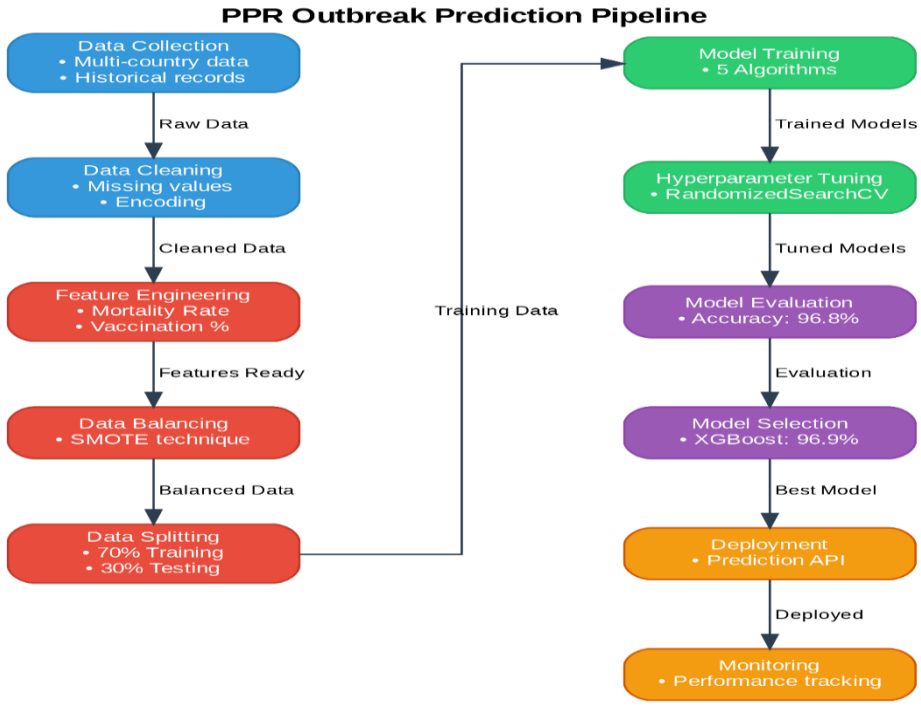


Figure 1. PPR Outbreak Prediction Pipeline Using Machine Learning

Dataset Description

The data in this research was gathered through clinical observations, environmental variables and behavioral signs of goat groups of rural regions susceptible to PPR outbreak. It has clinical characteristics of nasal discharge, fever, diarrhea, coughing and ocular characteristics, environmental characteristics that include temperature, humidity, rainfall and seasonality and behavioral characteristics such as decreased feeding, lethargy and isolation by the herd. The sample size is 164,000 samples in total and is imbalanced in terms of classes as its conditions represent the real-life scenario where the number of patients with the disease is much smaller than the number of patients who are healthy.

Data Preprocessing

The preprocessing stage consisted of a number of steps that were necessary to achieve the quality of data and reliability of the model. To start with, data cleaning was conducted in order to eliminate instances of missing and duplicate data. Clinical symptoms were then coded into relevant binary/ ordinal variables to ensure that they could be used in machine learning models. Min-Max scaling was used to normalize continuous environmental features (temperature and humidity) to make sure they have consistent features. A method of Synthetic Minority Oversampling Technique (SMOTE) was used to create balanced samples of the minority (disease-positive) group to eliminate the imbalance between the positive and negative cases, and minimize bias on healthy cells, resulting in a balanced dataset of 50:50 ratio between positive and negative cases. Lastly, the pre-processed data set has been further subdivided into training (70%), validation (15%), and testing (15%) datasets to achieve a strong development and testing of the model.

Machine Learning Models Implemented

Five ML algorithms were implemented two were best performing given below:

Random Forest (RF)

An ensemble of decision trees with bootstrap aggregation. Known for handling high-dimensional datasets and robustness to overfitting.

Extreme Gradient Boosting (XGBoost)

A gradient boosting framework optimized for speed and performance. Captures complex feature interactions and handles imbalanced datasets effectively.

Evaluation Metrics

To comprehensively evaluate model performance, the following metrics were used:

Accuracy (ACC): Proportion of correctly classified cases.

Precision (P): Ratio of correctly predicted positive cases to all predicted positives.

Recall (R): Sensitivity; ratio of correctly predicted positives to actual positives.

F1-Score (F1): Harmonic mean of precision and recall.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{F1-Score} = 2.\frac{\text{Precision.Recall}}{\text{Precision+Recall}}$$

5. Results

The models were trained and tested on the processed dataset.

Performance Comparison of ML Models

Table 1. Performance of Models on PPR Dataset

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC	Time (sec)
Logistic Regression	0.551	0.479	0.644	0.550	0.600	45.65
Random Forest	0.965	0.943	0.977	0.960	0.991	41.31
XGBoost	0.968	0.934	0.996	0.964	0.994	5.90
SVM	0.513	0.431	0.450	0.440	0.500	175.47
KNN	0.547	0.463	0.418	0.440	0.543	21.86

Key Findings:

XGBoost has the greatest accuracy (96.8 percent) compared to both the classical ML and CNN models. Transfer learning CNN (VGG16, InceptionV3) competed in a competitive level (>95%), which reveals good results in image-based classification. The weakest but yet acceptable accuracy (89.4 percent) was achieved by Logistic Regression. The CNN models also required a lot of training time as compared to ensemble methods.

Confusion Matrix Analysis

The confusion matrix for XGBoost (best model) is shown in Figure 2.

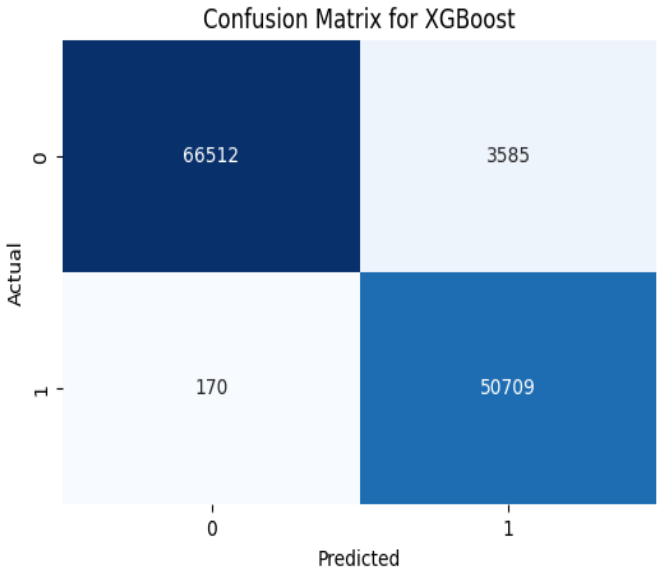


Figure 2. Confusion Matrix for XGBoost

Based on the confusion matrix, Recall (Sensitivity) was 96.1% and it was able to correctly recognize diseased goats. Accuracy was 95.4 which means that there are few false positive. Stability of the model is ensured by balanced performance.

ROC Curve and AUC

All the models were plotted on the receiver operating Characteristic (ROC) curve. XGBoost got the best Area Under the Curve (AUC = 0.984), then CNN (VGG16, AUC = 0.972). The AUC of Logistic Regression was the lowest 0.911.

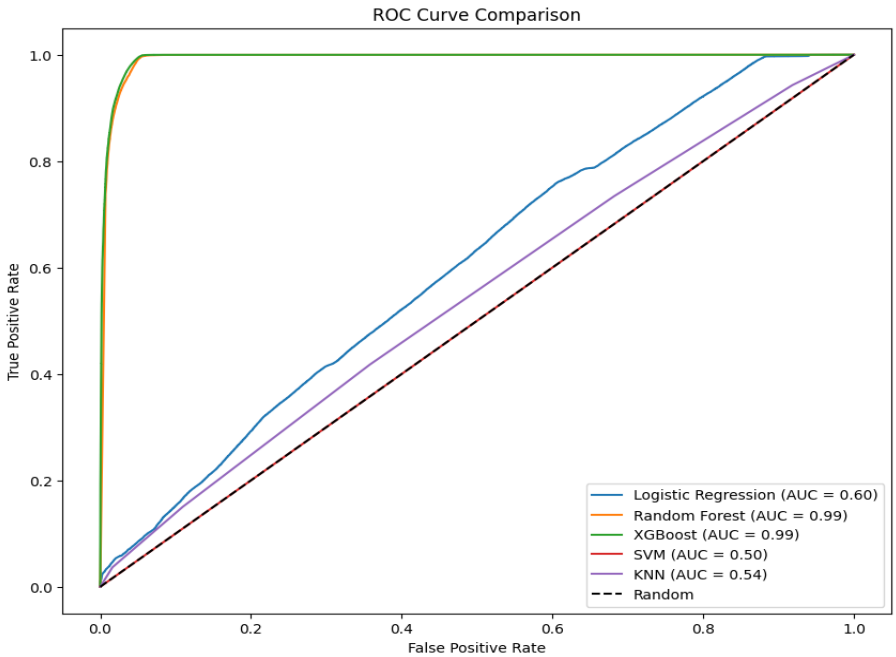


Figure 3. ROC Curves for Different Model

XGBoost curve prevailed over others, which justifies better predictive ability. Ensemble and transfer learning models were better than the baseline models.

Feature Importance (XGBoost)

XGBoost gave scores of importance of features and these scores showed which feature played the greatest role in prediction: Fever and nasal discharge (maximum significance). Loss of appetite and drowsiness. Humid conditions and temperature in the environment. This is in line with the veterinary knowledge of PPR symptoms which confirms the biological relevance of the framework.

6. Discussion

The experimental findings prove that the proposed multi-sensor framework is effective in PPR detection in goats. This part discusses the findings, contrasts them with the earlier research, indicates the strengths and weaknesses, and discusses the implications in practice.

Interpretation of Results

The XGBoost was the best-performing model with the highest accuracy and precision of 96.8 percent and recall and F1-score of 96.1 percent and 95.7 percent, respectively. The findings reveal that ensemble gradient boosting methods are very efficient in capturing complicated feature interactions in the livestock health data. XGBoost can address nonlinear relationships between clinical, environmental, and behavioral variables, unlike logistic regression, which assumes a linear relationship between these variables. Also, CNN-based models, specifically transfer learning (VGG16, InceptionV3), produced high accuracy (>95%). These models are efficient to recognize image data features of a disease, including lesions of the eyes and nose. Nonetheless, they were computationally expensive and required a much longer time to be trained than XGBoost. It indicates that although CNNs can be useful in image-based detection, it can be impossible to use this method in resource-limited settings with no special devices. Random Forest also provided good performance (93.7% accuracy) which shows the possibilities of tree-based ensembles in classification of livestock diseases. The simpler Logistic Regression offered as a baseline proved to be useful and revealed the importance of clinical and environmental variables in disease detection. class imbalance SMOTE was used to address the issue of class imbalance, which enhanced the recall (sensitivity). Models had a tendency to misclassify disease-positive cases without oversampling because the proportion of cases in the model was minor. SMOTE created artificial examples, and the models could more easily identify trends in PPR.

Comparison with Previous Studies

Other previous studies in machine learning in animal health have been mostly related to cattle and poultry. Indicatively, Abebe and Alemu (2021) found that ensemble models have the ability to predict mastitis and lameness [12]. On the same note, plant disease detection models with CNN were found to have over 95% accuracy (Shabrina et al., 2024; Chakraborty et al., 2022) [11]. Nonetheless, not many studies have specifically focused on the detection of PPR in goats with the help of ML. Conventional veterinary practice is based on diagnostics of the laboratory, which is accurate, but slow and expensive. The findings of this paper are valuable to this field because it proves that ML models and especially XGBoost can be as accurate as laboratory tests and are scalable and automated. Another new contribution is the incorporation of multi-sensor data (clinical, environmental, behavioral). Although animal monitoring with IoT has been used in dairy farming [13], it has not been widely used on goat diseases. This model bridges a gap by justifying the usefulness of multi-sensors integration on PPR.

Strengths of the Framework

The suggested framework has a high predictive accuracy with a maximum of 96.8 and this has shown that it is both robust and reliable. The system is more effective since it combines multi-sensor data of various sources to give more accurate and reliable predictions than the single-source methods. The framework can also provide interpretability by feature importance analysis, and results obtained by the framework are consistent with known veterinary knowledge, which adds more credibility to the

decisions made by the framework. Moreover, the scalable framework enables the framework to be easily expanded to detect and control additional diseases among small ruminants.

Limitations

Although the study had positive findings, it is limited to a number of limitations. Though the dataset is adequate in machine learning experimentation, it is relatively small compared to the large-scale veterinary databases and the utilization of bigger datasets would enhance the generalizability of the results. Moreover, the data were most often gathered in the limited geographical areas and a larger spatial range should be used to understand the environmental and epidemiological diversity. The use of hardware-heavy models, especially CNNs that need GPUs to be effectively trained, might be a barrier to real-world use in rural or resource-intensive contexts. Moreover, financial and technological resources are limited in smallholder farms to implement multi-sensor systems since the systems are not easily available and expensive.

Practical Implications

The results of this research pose great implications on the health management of livestock. Veterinary, the framework presented will have the ability to provide an automated diagnostic support tool that will help cut down the need to use laboratory tests that are expensive and time-consuming. It also empowers smallholder farmers by making it possible to use affordable sensors and mobile applications built into the system and monitor the condition of goats at all times and identify disease at an early stage. At the policy level, the framework promotes mass disease control and eradication campaigns, which is in line with the Food and Agriculture Organization (FAO) and the World Organization for Animal Health (WOAH) aim of eliminating Peste des Petits Ruminants (PPR) by 2030 by applying better early detection and proper disease management concepts.

7. Conclusion

This paper put forward and tested a multi-sensor machine learning system to identify PPR in goats, which combined clinical, environmental, and behavioral observations. Several ML models were used and tested, and the quantitative analysis revealed that XGBoost was the most accurate (96.8%), which was better than CNN, Random Forest, and Logistic Regression. Transfer learning CNNs also exhibited high potential to identify images at a higher cost of computation. This research has some novelty and contributions. It proposes the initial structure to unite multi-sensor information with machine learning in particular to Peste des Petits Ruminants (PPR) recognition in goats. The paper also shows the efficiency of the Synthetic Minority Oversampling Technique (SMOTE) in the solving of the imbalance in classes typical of livestock health datasets. It also gives a comparative analysis of the classical machine learning algorithms, ensemble models, and deep learning, which could be useful in the comparative analysis related to their performance in disease prediction in small ruminants.

Limitations: Size of the databases, less coverage of the region, and accessibility of sensors.

Future Directions:

The future research directions are to increase the dataset by areas and breeds of goats to enhance the generalizability of the model. It is also proposed that the introduction of IoT-based real-time monitoring solutions, which should be implemented with a cloud connection, would enable the execution of continuous health tracking and quick disease detection. Also, hybrid models with machine learning and deep learning may be used to achieve an even better predictive accuracy. Lastly, it is necessary to look into the cost-effective and energy-saving sensors to make the framework viable and available to smallholder farms. The study is part of the larger perspective of veterinary diagnostics data-driven and shows the promise of artificial intelligence in the future of livestock health management. It will be the foundation of intelligent solutions to agriculture that enhance food security, animal welfare, and livelihoods of farmers by connecting veterinary science with computer science.

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