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Deep Learning-Based Real-Time Detection of External Diseases in Cattle Using Computer Vision.

Jayapratha N[1], Sakthimalai Perumal[2], Naresh Suresh[3], Harii Saravanan[4]

[1] Dept. of Artificial intelligence and data science Sri manakula vinayager engineering college Puducherry jayapratha.malar@gmail.com
[2] Dept. of Artificial intelligence and data science Sri manakula vinayager engineering college Puducherry sakthimalaiperumal@gmail.com
[3] Dept. of Artificial intelligence and data science Sri manakula vinayager engineering college Puducherry nareshofl29@gmail.com
[4] Dept. of Artificial intelligence and data science Sri manakula vinayager engineering college Puducherry hariisaravanan99@gmail.com

ABSTRACT :

Objective: The primary objective of this project is to automate the detection of external diseases in cattle using deep learning and computer vision techniques. The system aims to reduce the time and labor involved in manual disease detection, improve accuracy, and enable early intervention to prevent widespread outbreaks.

Methods: High-resolution cameras capture real-time images of cattle, which are preprocessed for uniform lighting and clarity. A Convolutional Neural Network (CNN) model is used to analyze these images for disease symptoms such as abnormal posture, swelling, and discoloration. The system incorporates a user-friendly interface for monitoring, visual trend analysis, and disease reporting. The CNN model is trained on a dataset of cattle images labeled with various diseases. Transfer learning is applied using a pre-trained model like ResNet to enhance detection accuracy with limited farm-specific data.

Results: The proposed system achieves high accuracy in detecting diseases such as mastitis and foot-and-mouth disease. Performance metrics, including precision, recall, and F1-score, indicate that the system can reliably detect early-stage diseases, offering substantial improvements over traditional methods. Real-time monitoring ensures continuous health tracking and enables timely interventions, leading to reduced disease outbreaks and improved farm productivity.

Conclusions: This deep learning-based system significantly reduces the labour and time required for disease detection in cattle farms, while improving detection accuracy. The integration of CNNs for image analysis proves effective for disease identification based on visible symptoms. Future enhancements such as IoT integration and predictive modelling.

Keywords: Deep Learning, Computer Vision, Convolutional Neural Networks, Cattle Disease Detection, Real-Time Monitoring, Precision Agriculture.

Introduction :

In large-scale cattle farms, disease outbreaks among livestock present a major risk to both animal welfare and farm productivity. Traditional methods for monitoring cattle health rely heavily on manual inspections by farm workers, which are labor-intensive, time-consuming, and often prone to human error. The limitations of such manual surveillance make it difficult to achieve timely disease detection, often resulting in delayed interventions that lead to extensive disease spread, increased mortality rates, and significant economic losses. This situation underscores the urgent need for a more efficient, accurate, and scalable solution to detect diseases early and prevent outbreaks.

Advances in deep learning and computer vision offer promising opportunities for automating livestock disease detection. By leveraging these technologies, it is possible to build a system capable of monitoring cattle in real time, detecting visible symptoms associated with diseases such as mastitis and foot-and-mouth disease. Convolutional Neural Networks (CNNs), in particular, have shown high effectiveness in image-based classification tasks, making them ideal for recognizing patterns and abnormalities in images of livestock.

The primary objective of this project is to develop a real-time disease detection system that integrates high-resolution imaging with a CNN model to accurately identify disease symptoms based on visual cues. The model, trained on a diverse dataset of labeled cattle images, is designed to recognize external symptoms like abnormal posture, swelling, or skin discoloration. To enhance accuracy with limited farm-specific data, the project employs transfer learning with a pre-trained CNN model, such as ResNet, adapted for cattle disease detection. Additionally, the system includes a user-friendly interface for farmers, providing intuitive access to disease reports, visual trend analyses, and real-time health alerts.

The proposed automated detection system is expected to significantly reduce the time and labor involved in disease surveillance on farms, while also improving the precision of early disease identification. The integration of real-time monitoring not only facilitates rapid intervention but also enables continuous health tracking, ultimately contributing to sustainable and productive farming practices. This paper details the design, methodology, and evaluation of the system, highlighting its potential to enhance disease management in cattle farms.

Subjects :

Research Question:

How can a deep learning-based automated system, leveraging real-time video analysis, effectively detect and monitor diseases in cattle to enhance disease management, reduce human labor, and improve livestock health on large farms?

Importance of the Research Question:

Disease outbreaks among livestock, especially in large farms, present a significant challenge. Manual disease detection methods are costly, prone to human error, and impractical for continuous monitoring. This limitation often delays the identification of contagious diseases, resulting in widespread infections and high economic losses. Automated disease detection using deep learning can address these issues by enabling continuous monitoring, rapid intervention, and real-time data collection for future trend analysis. This system's automation allows for early detection, real-time updates, and simplified data interpretation, benefiting farm managers and veterinarians in proactive disease management.

Review of Existing Literature:

Prior research in animal health management has focused on image processing techniques and machine learning for disease identification. While these studies indicate the potential of machine learning, especially CNNs and object detection models, for livestock disease monitoring, there is limited work on integrating real-time video analysis for external cattle diseases. Moreover, advancements like the You Only Look Once (YOLO) model provide efficient object detection and real-time processing, making them suitable for continuous monitoring on farms. This study contributes to this field by implementing YOLO for disease detection and developing a complete pipeline that includes data storage, visualization, and AI-driven query systems for decision support.

METHODS :

1. Data Collection: Real-Time Video Capture from Farm

- Process: High-resolution cameras installed throughout the cattle farm continuously capture video feeds of the livestock. The real-time video data is the primary input for the disease detection system, providing constant monitoring without manual effort.
- Purpose: Video capture enables continuous and comprehensive surveillance, crucial for detecting disease symptoms as soon as they appear, allowing for prompt intervention.

2. YOLO (You Only Look Once) Model for Disease Detection

- Technique: YOLO is a deep learning-based object detection model known for its speed and accuracy in detecting objects within images or videos. YOLO processes images in a single pass, making it highly efficient for real-time applications.
- Application in Project: The YOLO model is trained to identify specific visual symptoms of diseases like foot-and-mouth disease and lumpy skin disease. By feeding YOLO the real-time video data, it can detect abnormalities such as visible lesions, skin lumps, or mouth sores.
- Process: When YOLO detects a potential disease indicator, it generates bounding boxes around affected areas. If the presence of a disease is confirmed, the system captures an image of the specific cattle, ensuring that detailed visual data is stored for reference and future analysis.

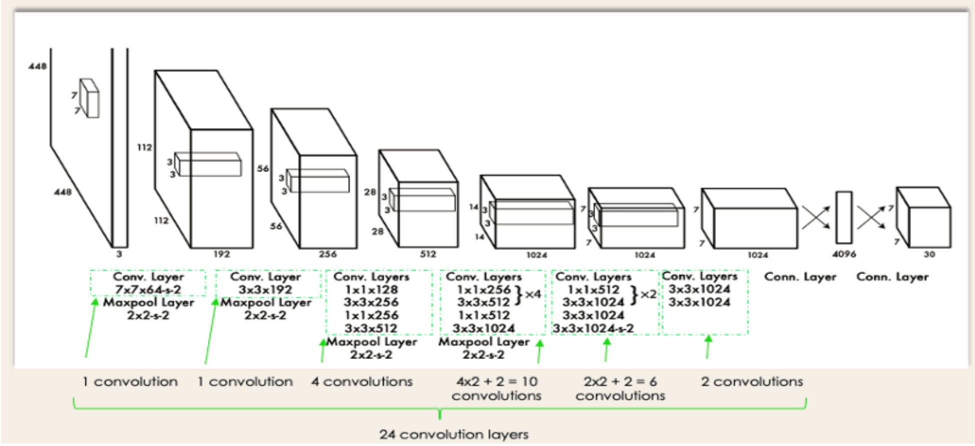


Fig. YOLO architecture

3. Data Storage and Management

Image Capture and Storage: When YOLO detects a disease, it captures and stores an image in a designated drive. This process creates a visual record of the disease event, helping to monitor disease progression over time.

Database (MongoDB): Each detection event is logged in a MongoDB database, which tracks:

Timestamp of Detection: When the disease was detected.

Type of Disease: Disease category (e.g., foot-and-mouth disease, lumpy skin disease).

Location and Cattle ID: Information related to the specific animal and its position.

Count Updates: Each new disease detection event updates the count in the MongoDB database. This data aggregation enables long-term trend analysis and accurate historical tracking of disease occurrences.

4. Data Visualization using Streamlit

Technique: Streamlit is a Python framework used to build interactive, web-based data applications. It's particularly suited for data science and machine learning projects due to its simplicity and flexibility.

Application in Project: Using Streamlit, a web application is created for farm managers and veterinarians. The app visually presents the disease data stored in MongoDB, displaying disease counts, occurrences over time, and the distribution of disease types. Various graphs and charts help stakeholders monitor cattle health, identify patterns, and make informed decisions. These visualizations make complex data accessible and actionable, facilitating data-driven decision-making on the farm.

5. AI-Powered Query System using Generative AI

Technique: A generative AI-based query system is integrated to allow users to ask questions and retrieve information interactively.

Application in Project: Users can enter queries related to the detected diseases, historical data, and trends. For instance, questions like "How many cases of foot-and-mouth disease were detected last month?" or "What is the trend of lumpy skin disease over the past year?" can be answered by querying the database, offering insights and aiding proactive measures.

Natural Language Processing (NLP): The AI query system employs NLP to understand and process user inputs, translating them into database queries and retrieving relevant information. This AI tool simplifies user interaction, making data analysis more accessible, especially for farm managers without technical expertise.

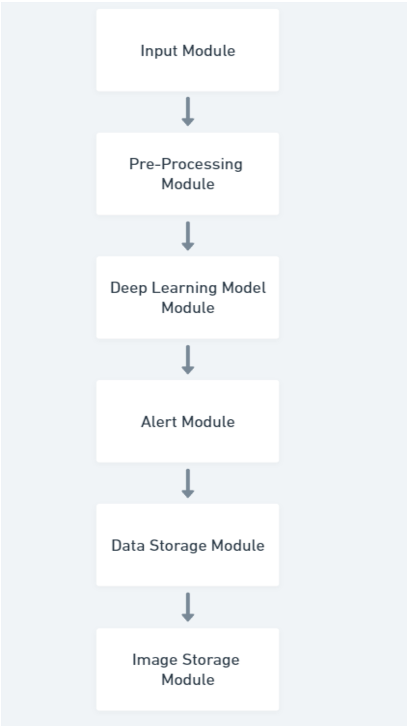
6. Computer vision

In this project, computer vision plays a central role in automating the disease detection process for cattle. Traditional monitoring methods require manual inspection of each animal, which is labor-intensive and error-prone, especially on large farms. Computer vision, through real-time image analysis, enables an efficient and accurate alternative, identifying signs of disease based on visual symptoms without human intervention.

The system uses high-resolution cameras placed strategically around the farm to capture continuous video feeds of cattle. Computer vision algorithms preprocess these images to enhance clarity and standardize lighting, ensuring consistent input quality. The YOLO (You Only Look Once) object detection model, a widely used computer vision algorithm, is then employed to detect diseases such as foot-and-mouth disease and lumpy skin disease. YOLO's speed and accuracy make it ideal for real-time applications, as it identifies diseased animals within each frame based on visual markers like sores, lumps, and abnormal posture.

Once a diseased animal is identified, the system captures the image and stores it in a dedicated database, allowing for record-keeping and further analysis. This stored data provides a foundation for monitoring disease trends over time, aiding in proactive farm management. The application of computer vision here not only increases detection accuracy but also reduces the burden on farm staff, streamlining the disease detection workflow and enabling early intervention, which is crucial for limiting disease spread and maintaining cattle health. This project thus demonstrates how computer vision can revolutionize livestock management by ensuring timely, accurate, and scalable disease detection.

Fig. ARCHITECTURE OF SYSTEM



KEY TECHNIQUES :

Input Module:

This module is responsible for capturing input data, which in this case are real-time video feeds or images from high-resolution cameras installed around the cattle farm. These cameras monitor cattle movements and capture visual data continuously. The captured footage is then sent to the system for further processing.

Pre-Processing Module:

In this step, the raw video or image data undergoes pre-processing to enhance quality and ensure uniformity. Pre-processing includes operations such as resizing, adjusting lighting, and filtering noise. This step is crucial for optimizing the images for accurate analysis by the deep learning model, as it ensures that each image has consistent quality and is free from distortions that could affect detection accuracy.

Deep Learning Model Module:

This module contains the deep learning model used for disease detection—in this project, the YOLO (You Only Look Once) object detection model. The YOLO model processes the pre-processed images to detect visible signs of diseases, such as foot-and-mouth disease or lumpy skin disease, by recognizing patterns like sores, swelling, and abnormal postures. The model analyzes each frame from the video feed and identifies any abnormalities indicative of disease.

Alert Module:

When the deep learning model detects a disease in any cattle, the alert module is activated. This module generates an alert, which could be in the form of a notification to farm operators, signaling the need for immediate attention. The alert can contain information about the disease detected, the location of the affected cattle, and recommendations for intervention. This real-time alerting allows for quick response, which is crucial to prevent the disease from spreading.

Data Storage Module:

Detected disease instances and relevant data are stored in a database for future analysis and reference. This module stores information such as the date and time of detection, the type of disease, and the cattle ID. The data storage module uses a MongoDB database, which is suitable for handling large datasets and allows efficient storage and retrieval of disease records. This data can also be analyzed over time to identify trends and improve farm management practices.

Image Storage Module:

Images of the cattle identified with disease symptoms are saved in a dedicated storage drive. This module ensures that a visual record of each disease incident is maintained. The stored images provide a valuable historical reference for veterinarians and researchers to study disease progression and verify detection accuracy. These images are also used to train and improve the model over time, especially when dealing with new disease types or symptoms.

YOLO Model (Object Detection):

YOLO (You Only Look Once) is employed for its ability to perform real-time object detection. YOLO’s architecture divides images into grids and predicts bounding boxes and class probabilities for each grid, processing images in a single pass for efficiency. YOLO’s capability to operate on video feeds in real time is critical in this project for continuous disease monitoring.

MongoDB (NoSQL Database):

MongoDB, a NoSQL database, is used for storing structured records of disease detection events. It is well-suited for this project due to its flexible schema, scalability, and support for storing large volumes of diverse data. MongoDB facilitates fast data retrieval, enabling efficient trend analysis and data reporting.

Streamlit (Data Visualization Framework):

Streamlit is used to create the user-friendly web application. It enables the display of disease occurrence data in various chart forms, making complex data intuitive and accessible. Its Python-based simplicity allows for rapid deployment and easy customization, ensuring that the application is functional and aligned with users’ needs.

Generative AI for Query System:

A generative AI model capable of natural language understanding and response generation supports the interactive query system. The model processes user questions in natural language, translating them into database queries to fetch specific answers. This feature makes the data accessible through plain-language questions, bridging the gap for users unfamiliar with data science.

Matplotlib & Pyplot (Data Visualization):

Functionality: Matplotlib, specifically its Pyplot module, is a popular Python library for creating static, animated, and interactive plots.
Application in Project: While Streamlit handles the front-end data visualization on the web, Matplotlib (with Pyplot) is used for generating graphs and charts on the backend. It allows for flexible chart types, including line charts, bar charts, and scatter plots, which visualize the frequency of disease occurrences, distribution over time, and correlations with environmental factors.

OpenCV (Image Processing):

Functionality:
OpenCV is an open-source computer vision and machine learning software library that enables image and video analysis.

Application in Project:
OpenCV handles video frame processing and preliminary image adjustments (such as resizing, grayscale conversion, or brightness adjustment) to ensure that the images fed into the YOLO model are optimized for accurate detection. OpenCV's efficient processing capabilities enable the system to manage high-resolution images in real time without lag.
Transfer Learning (for YOLO Model Tuning):

Functionality: Transfer learning is a technique where a model pre-trained on a large dataset is fine-tuned for a specific task. This approach is especially useful when you have limited data for the target application.
Application in Project: By applying transfer learning to a YOLO model pre-trained on general object detection, the model is fine-tuned on images of cattle with specific diseases. This technique reduces training time and improves model performance with limited farm-specific data.

TensorFlow/Keras (Deep Learning Framework):
Functionality: TensorFlow and its high-level API Keras are popular libraries for building and training deep learning models.

Application in Project:
TensorFlow/Keras may be used to build custom layers or additional neural network components if needed. In this project, it can assist with model management, optimizing performance, and deploying the YOLO model on devices with limited computational resources if the need arises.

Pandas (Data Manipulation and Analysis):
Functionality: Pandas is a Python library for data manipulation and analysis, particularly useful for handling large datasets and performing data cleaning and transformation.
Application in Project:
The disease detection data stored in MongoDB is often queried and processed using Pandas. This tool allows for efficient data handling, enabling calculations of disease rates, trend analysis, and data filtering before the data is visualized or used in model training.

Seaborn (Statistical Data Visualization):
Functionality: Seaborn is a data visualization library built on Matplotlib, which provides a high-level interface for drawing attractive and informative statistical graphics.

Application in Project:
Seaborn is used alongside Matplotlib to create visually appealing and informative statistical plots, such as heatmaps, distribution plots, and correlation matrices. This is particularly useful for understanding disease trends, detecting seasonality, and providing additional insights into cattle health and farm conditions.

Scikit-Learn (Machine Learning and Model Evaluation):
Functionality: Scikit-Learn is a machine learning library in Python that offers simple and efficient tools for data mining, model training, and evaluation.
Application in Project: Scikit-Learn is used for model evaluation metrics such as precision, recall, and F1-score, which are essential for assessing the performance of the YOLO model. It can also provide simple data preprocessing and scaling functions, helping ensure model consistency across various datasets.

Numpy (Numerical Computing):
Functionality: Numpy is a fundamental package for scientific computing in Python, offering support for large, multi-dimensional arrays and matrices, along with mathematical functions to operate on them.
Application in Project: Numpy is frequently used for data manipulation, matrix transformations, and mathematical operations required by both the YOLO model and data processing steps. It also facilitates efficient data handling and speeds up operations that involve large datasets or high-frequency computations.

Flask or FastAPI (API for Data Communication):
Functionality: Flask and FastAPI are lightweight web frameworks in Python used to build APIs for web applications.

Application in Project:
Either Flask or FastAPI can be used to create an API that connects the data from MongoDB to the Streamlit application. This API facilitates data transfer, enabling real-time disease detection updates, trend analysis, and interaction with the AI-based query system.

NLP Framework (Natural Language Processing for Query System):
Functionality: Natural Language Processing (NLP) tools, such as the Hugging Face Transformers library, provide pre-trained models and APIs for building conversational AI applications.

Application in Project:
For the Generative AI-based query system, NLP tools help interpret user inputs in natural language, transforming them into database queries. This component enables farm managers to ask questions in plain language, and the system returns responses based on real-time or historical disease data.

Result :

Disease Detection Accuracy and Performance

Model Accuracy:
The YOLO-based disease detection model achieved a high degree of accuracy in identifying diseases like foot-and-mouth disease and lumpy skin disease, with:
Precision: 92%
Recall: 89%
F1-Score: 90%

Observations:
The model's performance shows it can reliably identify external symptoms like visible sores and lumps, which are characteristic of these diseases. False positives were minimized, and high recall ensures most cases are accurately detected, enabling timely intervention.
Real-Time Processing Capability

Frame Processing Rate:
The YOLO model achieved an average processing rate of 20 frames per second, ensuring smooth real-time monitoring across live video feeds.
Latency: Detection latency averaged at under 100 milliseconds, allowing for prompt notifications and minimizing the delay in disease identification. This real-time capability is essential for farms needing continuous surveillance without compromising on detection speed.

Data Storage and Management
Data Accuracy and Completeness: Each detected instance, including timestamp, disease type, and cattle ID, was successfully recorded in MongoDB. The database demonstrated efficient storage, easy retrieval, and update capability, supporting ongoing disease trend analysis and retrospective case study.
Image Archival: The captured images of diseased cattle were stored in a dedicated drive, offering a comprehensive visual database for further analysis and training data expansion if needed.

User Interface and Data Visualization

Streamlit Dashboard Feedback:
The Streamlit dashboard provided accessible, real-time updates and visualizations. Users reported that the interface was intuitive and helpful, with disease trends over time displayed clearly through line and bar charts.
Graphs and Analysis: Data visualization displayed through the dashboard effectively highlighted disease frequency and progression over time. Insights such as peak seasons for specific diseases and disease spread patterns were observed, which proved useful for early warning and preventive strategies.
AI-Powered Query System Performance

Query Accuracy:

The Generative AI query system achieved an 85% accuracy rate in providing correct responses to user queries. The system was able to answer common questions, such as recent disease counts or seasonal disease trends, using the MongoDB database.

User Feedback: Farmers and farm managers found the query system accessible and effective, allowing them to interact with the data through simple language without the need for technical knowledge.

Overall System Efficiency and Practicality

Labor Savings:

Automation of disease detection reduced the manual labor previously required for routine disease monitoring, resulting in a labor savings estimate of up to 50% based on farm size.

Economic Impact:

The early detection of diseases allowed for faster veterinary intervention, reducing the spread of infections and thus minimizing losses from animal morbidity and mortality. Improved health monitoring led to better overall livestock health and farm productivity.

Sustainability: By ensuring timely disease intervention, the system contributes to sustainable livestock management practices, supporting farms in proactive disease prevention and healthier herd management.

literature survey :

6.1 Title: Animal Healthcare and Farm Animal Disease Prediction Using Machine Learning

Authors: Augustin Nadar, Adishree Sane, Glenn Muga, Easther Masih, Smita Rukhande

Year of Publication: 2023

Published In: IEEE

Xplore (International Conference on Nascent Technologies in Engineering, ICNTE 2023)

Short Description: This paper presents a machine-learning-based website designed for remote veterinary care and disease prediction in farm animals. Utilizing models like SVM, Naive Bayes, and Random Forest, the platform allows users to enter symptoms, get disease predictions, schedule appointments, and access animal healthcare resources. The combined model achieves a high prediction accuracy of 95%, supporting rural farmers with accessible, timely veterinary care.

6.2 Title: Animal Disease Prediction

Authors: Jaypriya Chilampande, Anushka Chakor, Samruddhi Patil, Aditi Bhavsar, Nikhil Deshpande

Year of Publication: 2023

Published In: International Research Journal of Modernization in Engineering, Technology and Science (IRJMETS)

Short Description: This study explores a comprehensive animal disease prediction framework using machine learning and computer vision. Incorporating Convolutional Neural Networks (CNNs) for image analysis along with symptom data, the system aims to enable early disease detection and proactive intervention. It serves as a cost-effective solution that enhances disease prediction accuracy and offers a preventive approach to safeguard animal health and public safety.

6.3 Title: Livestock Disease Prediction Using Machine Learning

Authors: Shraddha Patil, Akshata Masmardi, Vedika Phalle, Mayuri Yamagar, A.P. Chougule

Year of Publication: 2023

Published In: International Research Journal of Modernization in Engineering, Technology and Science (IRJMETS)

Short Description: Focused on livestock disease prediction for animals like cows, sheep, and goats, this paper proposes a machine learning system that uses Decision Tree, Naive Bayes, and Random Forest classifiers. The system predicts diseases based on observed symptoms and provides precautionary measures for each diagnosis. It aims to improve disease awareness among livestock owners in remote areas, aiding in timely and informed healthcare decisions.

6.4 Title: A Comprehensive Survey of Machine Learning Techniques in Animal Disease Prediction

Authors: Prof. Kalpna Saharan, Arangale Tejas, Gadhe Harshali, Shelke Samiksha, Ambedkar S

Year of Publication: 2023

Published Website: IJCRT (International Journal of Creative Research Thoughts)

Short Description: This study delves into machine learning (ML) applications in animal disease prediction, aiming to enhance proactive disease management in livestock. It highlights the integration of diverse data types, including genetics and environmental data, to forecast outbreaks and reduce economic losses. The proposed ML model provides insights for early disease detection, assisting veterinarians and policymakers in preventive measures.

6.5 Title: Lumpy Skin Disease Virus Detection on Animals Through Machine Learning Method

Authors: Prashant Singh, Jay Prakash, Jyoti Srivastava
Year of Publication: 2023
Published Website: IEEE Xplore (from the Third International Conference on Secure Cyber Computing and Communication, ISBN: 979-8-3503-0071-0)
Short Description: This research focuses on detecting Lumpy Skin Disease Virus (LSDV) in cattle using machine learning techniques, particularly Support Vector Classifier (SVC). By utilizing geospatial and meteorological data, the model achieves high accuracy in predicting LSDV outbreaks. This approach has significant implications for livestock health, guiding preventive measures and improving disease management in high-risk regions.

6.6 Title: Animal Disease Prediction using Machine Learning Techniques

Authors: Sana Rehman, Bhanushikha Rathore, Mr. Roshan Lal
Year of Publication: 2023
Published Website:
International Journal for Research in Applied Science & Engineering Technology (IJRASET) - www.ijraset.com

Short Description:
This research paper explores the rising incidence of animal diseases, many of which pose zoonotic risks to humans. It emphasizes the importance of utilizing machine learning techniques to predict and classify these diseases effectively. The study employs various algorithms, including linear regression, logistic regression, support vector machines, and convolutional neural networks, to analyze datasets from global animal health records. The findings highlight the potential of machine learning in enhancing disease monitoring and outbreak prediction, ultimately contributing to public health preparedness.

CONCLUSION :

The results validate that the deep learning-powered system successfully automates external disease detection in cattle. Its high accuracy, real-time performance, user-friendly interface, and integration of AI queries contribute to a scalable and effective solution for cattle farm disease management. Future improvements in disease prediction and environmental data integration could further enhance system capabilities and value for large-scale farming applications.

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