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Intelligent Cattle Monitoring System Using IOT, Computer Vision and Deep Learning for Precision Livestock Farming

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Abstract - This advanced cattle monitoring system uses modern technologies such as computer vision and deep learning to help farmers manage their livestock more efficiently. It is particularly beneficial for farmers in remote regions, where access to veterinary support and timely assistance can be limited. The system performs multiple tasks, including identifying individual cows, managing automated feeding, monitoring shed temperatures, and sending timely vaccination alerts. One of its most important functions is the early identification of Lumpy Skin Disorders (LSD). LSD is a fast-spreading viral infection that can severely harm cattle health and cause major financial losses. The system includes a specialized detection module that examines images of cattle and recognizes early signs of the disease in real time. This quick identification allows farmers and veterinarians to take immediate action and prevent the infection from spreading across the herd. Beyond disease detection, the platform acts as a complete livestock management tool. It features a smart vaccination reminder system that automatically alerts cattle owners, generates individual vaccination schedules, and keeps track of upcoming doses. Additional features—such as cattle tracking, feeding automation, and continuous monitoring of environmental conditions inside the shed—help improve overall productivity and farm hygiene. By combining AI-based analysis, automated monitoring, and a simple, user-friendly interface, the system reduces manual labor and encourages more sustainable livestock practices. Ultimately, it supports the transition toward technology-driven, self-reliant farming in India, boosts farm productivity, strengthens rural livelihoods, and ensures better health and protection for cattle.

Keywords—YOLO, Computer Vision, image processing, Convolutional Neural Networks, Internet of Things, Lumpy Skin Disease (LSD).

I. INTRODUCTION

India's agricultural economy is one of the largest in the world, and livestock plays an essential role in supporting rural life. the latest survey reports indicate that more than one lakh cattle have died, creating severe financial strain for farming families. For many households, cattle are central to their daily activities as well as their income. They provide milk, contribute to food security, and produce manure that enriches soil for farming. Because of these benefits, millions of families rely on cattle as a dependable source of livelihood.

Despite their importance, livestock care in many regions still depends on traditional, manual methods. Farmers often rely on physical inspection and simple handwritten records, which are slow, unreliable, and unable to provide timely information. This makes it difficult for farmers to monitor their animals' health properly, especially in remote or low-income areas where access to resources is limited. Veterinary services are often far away or expensive, making disease control even more challenging. Due to these difficulties, many farmers miss routine vaccinations, allowing preventable diseases to reduce productivity and increase economic risk.

Lumpy Skin Disorder (LSD) has emerged as a major problem to cattle because it spreads rapidly through insect bites and frequently reoccurs. Infected animals experience a sharp drop in milk production and may even die if the disease becomes severe. Rural farmers are especially at risk because veterinary support is scarce. Traditional diagnostic methods rely on laboratory testing, which takes time and may not be affordable or reachable for many farmers. These delays make early detection difficult, leading to larger outbreaks and significant financial losses. Without timely diagnosis, livestock health systems become weaker and less effective.

Technology is helpful in overcoming these issues by providing automated alerts and reminders for feeding, vaccinations, and health monitoring through mobile phones or computers. In the absence of such integrated systems, farmers must manually maintain important details like vaccination dates and health records. This manual approach is time-consuming and often leads to errors or misplaced information. As a result, vaccinations are missed, signs of illness are overlooked, and preventive care becomes inconsistent.

These ongoing challenges highlight the need for modern, automated, and user-friendly tools that can simplify livestock management. Such technologies can greatly improve cattle health, reduce financial losses, and support farmers by making animal care more efficient and dependable in the long run.

II. Related Work

[1] In 2019, N. Shivaanivarsha, Pasupuleti Bhaskaran Lakshmidevi, and J. Tina Josie introduced a real-time cattle disease detection system developed by Convolutional Neural Networks (CNNs). Since cattle often experiences symptoms like photosensitization, papillomatosis, bovine mastitis, and lumpy skin disease, early diagnosis is essential for effective livestock care. Their work demonstrates how recent advancements in ConvNet technology can support veterinary applications. The team developed a mobile-based diagnostic tool that uses TensorFlow Lite and Google's Teachable Machine to classify diseases from images. The system focuses on four major cattle diseases and achieves an impressive accuracy of about 98.58%, highlighting its potential for field-level deployment.

[2] In 2020, Md. Ronny, Raid, and Zaid Hasan proposed a deep-learning solution for detecting external cattle diseases. These conditions—including Lumpy Skin Disease, Infectious Bovine Keratoconjunctivitis, and Foot-and-Mouth Disease—spread rapidly and pose global concerns. however CNNs are earlier used in computer vision, earlier research lacked a developed deep learning algorithm for identification of cattle disorder. The project aims to fill a gap by developing a real-time detection system that evaluates common external infections. Multiple CNN architectures such as VGG-16, Inception-V3, and a standard deep CNN are tested. The research details the full workflow, including data gathering, image preprocessing, and model evaluation.

[3] In 2021, Shivank Vyas, Nahant Dashi, and Vipin Shukla presented an IoT-based method for detecting mastitis and foot-and-mouth disease in dairy cattle. As Global demand for dairy products grows, monitoring cattle health has become more challenge,perticularly in South Asian countries like India, Nepal, Bhutan, Bangladesh, and Sri Lanka, where farmers often struggle with consistent animal health management. Their approach uses a network of sensors to collect physiological and behavioral data such as temperature, sound patterns, and movement. This information is then processed through a microcontroller and analyzed using neural-network-based machine learning algorithms to detect early indecations of sickness.

[4] Elias (2021) investigated how image processing and machine learning techniques can be used to identify lumpy skin disease in cattle. Ethiopia, home to one of the largest livestock populations in Africa, still depends heavily on manual disease detection, which limits overall productivity. Automated diagnostic systems offer clear benefits over traditional visual inspection. The study presents a structured image-analysis pipeline developed specifically for identifying lumpy skin disease in cows. during the preprocessing phase, each image is standardized to 200 × 200 pixels, denoised using Gaussian filters, and enhanced using histogram equalization to improve clarity.

From a total dataset of 1,740 images, 80% were allocated for training, and 20% for testing. The evaluation revealed that the SVM classifier performed the best, achieving an accuracy of 95.7%.

By comparison, the Random Forest model reached 87.4%, while the Softmax classifier achieved 94.8%. One of the main challenges noted in the research was the difficulty in obtaining consistently high-quality images suitable for accurate analysis.

[1] In 2022, Changwon Jiang, Changmin Hu, Hunching Chen, Shengsong Xiao, and Aizhen Gao proposed a rapid testing method for detecting the Lumpy Skin Virus (LSV) in cattle. Since LSD is a severe poxvirus infection capable of causing large-scale outbreaks, quick and reliable diagnosis is extremely important. Their study introduces an on-site detection system that includes recombinase polymerase amplification targeting the orf068 gene with a CRISPR-Cas12a-based fluorescent readout. The method demonstrates high sensitivity, detecting as few as five copies of the target gene per microliter in plasmid samples. It can also identify viral DNA at concentrations as low as 10^2 $TCID_{50}$ per milliliter. These findings indicate that the proposed assay is well-suited for field use and can support rapid identification of LSDV in real farm conditions.

[2] In 2024, Feng Hu, Ming Zhou, Yelling Qin, Yanking Xin, and Guiyang Li developed an IoT- and RFID-based system aimed at improving management practices on cattle farms. As global dairy production increases, maintaining consistent and accurate health monitoring has grown more challenging. Farmers often find it difficult to carry out all necessary evaluations manually. Diseases such as foot-and-mouth disease (viral) and mastitis (bacterial) remain major concerns for dairy herds. The system proposed in this work uses a range of IoT sensors to continuously collect physiological and behavioral data—including temperature changes, movement patterns, sound signals, and other indicators. These inputs are handled through a microcontroller and analyzed using neural-network-driven machine learning models, enabling early and reliable detection of cattle health problems.

III. METHODOLOGY

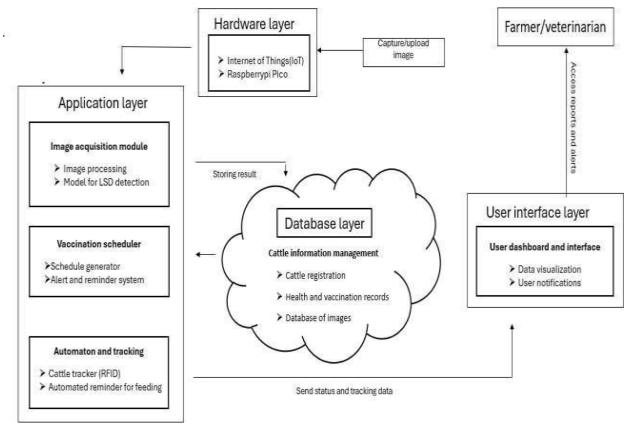


Fig. 1. Methodology

1. Hardware layer:

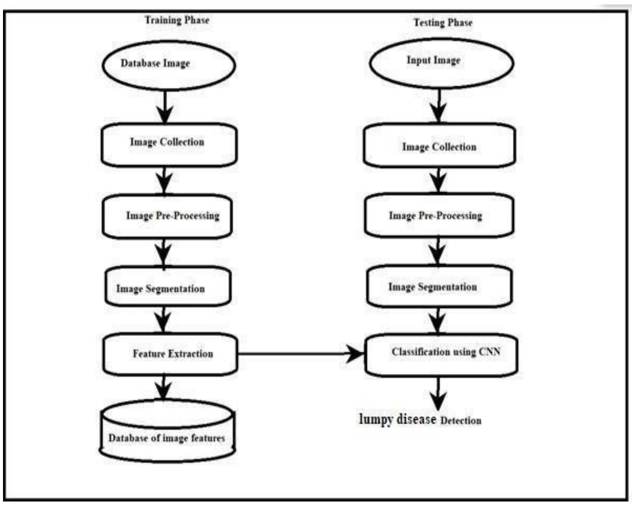
A camera or image sensor is used to capture skin images of the cattle so that different diseases can be identified. A Raspberry Pi handles automation processes and the transfer of data.

1. Application Layer:

Image Processing and Deep Learning Unit: This component uses a CNN model along with Open CV to analyze images and detect conditions such as lumpy skin disease. Cattle Automation and Tracking Unit: Includes systems for automated shed cleaning and location tracking using GPS or RFID. Health and Vaccination Management Unit: Maintains medical histories and helps farmers follow vaccination timelines. alerts and Notification Unit: Sends warnings about potential diseases and reminders for vaccinations through SMS, email, or an app.

2. Data Flow Layer:

The system follows a clear data workflow: images are first captured, then processed by an AI model for disease analysis, followed by health status updates and automated alerts. All results are stored in a database and can be viewed through a dashboard or delivered through voice notifications. Each stage functions independently, which simplifies the overall operation and allows separate testing of modules. The proposed architecture includes three main components—preprocessing, feature extraction, and disease identification. In the preprocessing phase, median filtering is applied to minimize image noise. The complete design includes image capture, cleaning, segmentation, feature derivation, model training, and final classification.



1. Image Collection

The dataset used in this project is sourced from publicly available online repositories. Although the selected set focuses on lumpy skin disease, the hosting platform also provides images related to other cattle diseases. The system captures images in a way similar to a magnifying tool, allowing close-up views comparable to X-ray visuals.

2. Image Preprocessing

The purpose of the preprocessing stage is to enhance important visual details while minimizing unwanted distortions in the images. This step ensures that the data is clean and suitable for later processing tasks. The preprocessing phase mainly involves three operations: converting images to grayscale, removing noise, and enhancing the overall image quality.

a) Grayscale conversion: Only brightness information is contained in a grayscale image. Each pixel value in a grayscale image represents an amount of light. In grayscale images, the brightness graduation can be distinguished. Only light intensity is measured in grayscale images. The brightness of an 8-bit image will vary between 0 and 255, with 0 denoting black and 255 denoting white. Grayscale conversion transforms color images into grayscale images.
b) Noise Removal: This technique seeks to identify and eliminate undesirable noise from a digital image. Determining which aspects of an image are real and which are the result of noise is a difficult task. Random fluctuations in pixel value make up noise.

3. Segmenting an image

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Segmenting the cervical tumor region from surrounding CT images came next after image preprocessing. A contrast-adjusted black-and-white image was produced to improve segmentation.

Image Enhancement:

The purpose of image enhancement is to refine the visual quality of an image so that important features stand out clearly. In this project, contrast adjustment is applied to generate a cleaner and more informative output.

1. Image Segmentation:

After preprocessing, the next step is to isolate the target region from the rest of the CT image. A contrast-improved grayscale version of the image is created to make the segmentation process more effective.

2. Feature Extraction:

Feature extraction plays an essential role in obtaining meaningful information from images. For texture-related analysis, the Gray Level Co-Occurrence Matrix (GLCM) is used to capture pixel-to-pixel spatial relationships. Using this matrix, key texture attributes such as contrast, entropy, energy, homogeneity, and correlation are calculated to represent the most significant characteristics of the image.

3. The training dataset:

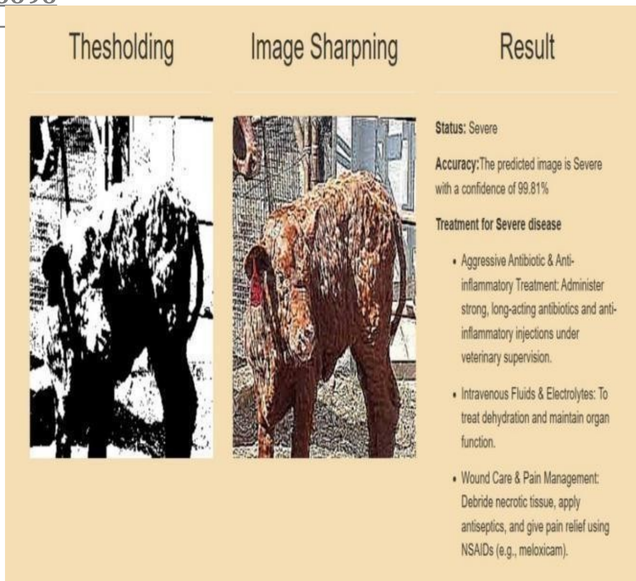
it is built using images that clearly represent various disease stages.

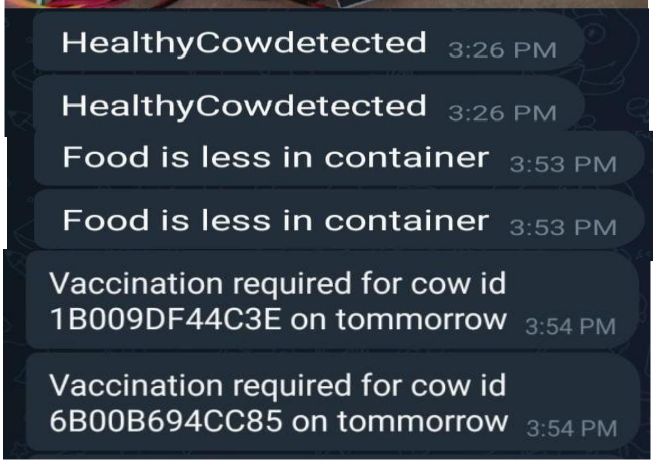
These labeled images are used to teach the classifier how to recognize patterns associated with each condition. A separate testing set is stored in a temporary directory to evaluate the model's performance. The predictions from the test samples, along with classifier output graphs and extracted feature sets, help refine the image-processing system for better accuracy.

4. YOLO-Based Classification:

YOLO (You Only Look Once) is one of the most popular and efficient deep-learning algorithms for visual recognition. It revolutionized the field by enabling real-time object detection with high precision. Unlike object detection tasks that locate specific items within an image, classification focuses solely on determining the overall category of an image. YOLO is widely used in situations where both speed and accuracy are essential.

RESULTS





CONCLUSION

This research represents an important step forward in the detection and classification of cattle skin disorders. It successfully distinguishes healthy skin from mild and severe affected cases, and it enhances the accurate identification of lumpy skin disease. The study provides three key contributions. First, it develops a dedicated image dataset created specifically for lumpy skin disease, which is vital for training advanced machine learning models. Second, it introduces a carefully structured classification system capable of evaluating skin images and determining the severity of infection with improved precision. Third, it proposes a method that uses real data collected from local farms to estimate the frequency of disease outbreaks, making the system more suitable for practical field use.

During the research process, two major difficulties were encountered. One major challenge was the presence of noise in the images, which made it harder to isolate and examine the infected areas on the cattle's skin accurately. Another challenge was the limited availability of high-quality, well-annotated images of lumpy skin disease, which reduced the diversity of training data required for robust model performance.

To overcome these challenges and strengthen livestock health monitoring, the study introduces an intelligent system powered by Internet of Things (IoT) technology. By combining deep learning models with computer vision methods, the system can automatically monitor cattle, interpret visual data, and deliver timely evaluations of their health status. This integration of IoT sensors, automated image analysis, and intelligent decision-making creates a comprehensive platform that supports farmers in managing cattle health more efficiently and with greater accuracy.

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