# Automation Based Innovative Solution for Cattle Livestock

Dr. Shubha  $P^1$ , Aishwarya R B<sup>2</sup>, Ananth Kumar Shinde V<sup>3</sup>, Apoorva A S<sup>4</sup>, Savitha R<sup>5</sup>

*<sup>1</sup>Asst Professor, Dept of Electronics and Instrumentation Engg, Dr Ambedkar Institute of Technology*

*Bengaluru*

*2,3,4,5VIII B E Students , Dept of Electronics and Instrumentation Engg, Dr Ambedkar Institute of Technology Bengaluru* 

*Abstract—***The Automation of Cattle Livestock initiative is a groundbreaking endeavor aimed at revolutionizing cattle care and management in nations where cattle are integral to rural economies. By addressing challenges such as limited veterinary access, delayed vaccinations, and disease outbreaks, this project employs cutting-edge technology to provide comprehensive solutions. Its intelligent vaccination scheduler tailors vaccination plans for individual cattle, while advanced image processing detects early signs of disease. With simplified registration through RFID tags, the project enhances accessibility and promotes sustainable cattle rearing, empowering farmers and safeguarding livestock. Ultimately, it represents a pioneering step toward a brighter future for both cattle and their caretakers, driving rural community development and ensuring the well-being of dependent communities.**

*Index Terms—***Radio Frequency Identification, Animal tracking, Disease detection, Live location.**

#### I. INTRODUCTION

The Automation of Cattle Livestock initiative is a transformative system designed to revolutionize cattle care and management through advanced technology. In rural economies where cattle are vital, the lack of accessible veterinary care, timely vaccinations, adequate feeding, and disease outbreaks pose significant threats to livestock health and the livelihoods of dependent communities. This system addresses these challenges comprehensively by leveraging innovative solutions. A key feature is the intelligent vaccination scheduler, which creates personalized vaccination plans based on individual cattle profiles and sends timely reminders to owners, ensuring vaccinations are not missed. Additionally, the system employs sophisticated image processing techniques to detect early signs of disease in cattle, enabling prompt intervention and treatment. By incorporating a simple RFID tagging system, the proposed system ensures easy registration and tracking of new cattle, enhancing accessibility and management. This initiative aims to improve cattle health, increase accessibility to essential services, and promote sustainable cattle rearing practices. The Automation of Cattle Livestock system's ultimate goals are to safeguard cattle, boost rural community development, and provide farmers more authority. For cattle as well as their caregivers, this innovative project is a big step towards a more promising and sustainable future.

# II. LITERATURE REVIEW

The author provides a comprehensive overview of the increasing significance of RFID technology in animal tracking across diverse economic sectors, emphasizing its pivotal role in understanding animal behavior, movement patterns, and health status. They delve into its applications in livestock husbandry, agriculture, and wildlife conservation. Through a systematic literature review, the study investigates the utilization of RFID technology in animal tracking, examining the range of animals tracked, the issues addressed, operating frequencies employed, as well as the incorporation of supplementary technology. In monitoring mammals' cattle being the most often watched animal livestock management becomes increasingly important. The prevalence of passive UHF tags in RFID technology is noted, often augmented by cameras and GPS[8] for more effective tracking capabilities. The author underscores the significance of early diagnosis in controlling highly contagious external diseases like Foot and Mouth Disease (FMD)[9], Lumpy Skin Disease (LSD), and Infectious Bovine Keratoconjunctivitis (IBK) in cattle.

The conventional Convolutional Neural Networks (CNN) are more used in image processing and computer vision than deep learning approaches in disease detection systems for livestock farms. Introducing a novel approach, the suggested framework utilizes various CNN architectures including conventional deep CNN, Inception-V3, and VGG-16 for early disease detection. The process is described in depth in the paper, from data collecting to the final result, demonstrating the system's effectiveness with a 95% accuracy rate. This advancement not only reduces human errors in disease identification but also aids veterinarians and husbandry farmers in recognizing diseases promptly, potentially transforming disease management practices in cattle farming. The author emphasizes the critical issue of cattle healthcare, particularly in burgeoning dairy industries such as India's, where diseases like Foot and Mouth Disease (FMD) and Mastitis pose significant threats to livestock health and economic stability. Proposing a solution, they advocate for the utilization of IoT technology for disease detection in cows. By employing sensors to monitor vital parameters such as temperature, motion, and sound, along with microcontrollers and machine learning algorithms like neural networks, the author aims to create a comprehensive system for early detection of FMD and Mastitis. By enabling farmers to keep an eye on and protect the health of their cattle, this creative strategy has the potential to lower financial losses and promote sustainable dairy farming methods.

Lumpy skin disease (LSD) is a highly impactful viral illness in cattle, caused by the Neethling virus strain within the Capri poxvirus genus. LSD, marked by fever, enlarged lymph nodes, and skin nodules, has spread beyond Sub-Saharan Africa to the Middle East, Asia, and Europe, resulting in significant financial losses in livestock [3] due to reduced milk yield, infertility, and trade restrictions. Originating in Ethiopia in 1983, LSD has after becoming widespread across the country, with numerous outbreaks recorded from 2007 to 2011, mainly in Oromiya. All cattle breeds and ages are vulnerable, with Bos Taurus more susceptible than Bos indicus. Factors such as diverse agro-climatic conditions, new animal introductions, and communal watering bodies aid LSD transmission, with mechanical insects and wildlife contributing.

Diagnosis involves serological and molecular techniques, with control strategies including mass vaccination, import restrictions, vector management, and culling infected animals as needed. The midland agro-climate zones have notably higher LSD prevalence due to increased mechanical vector insect presence.

#### III. METHODOLOGY

The key component of the disease detection system, including those designed to identify lumpy skin disease in cattle is the image input stage. It serves as a foundation for further investigation and is essential in evaluating the precision and dependability of the diagnostic procedure. When acquiring images for the purpose of identifying lumpy skin diseases, several factors need to be carefully considered in order to get the best results in terms of image quality and eligibility for additional investigation. Figure 3.1 shows the system's block diagram.



Fig 3.1 The block diagram of the designed system

Camera adjustments ensure high-quality images under varying lighting conditions. Proper posture aids accurate assessment. Pre-processing involves contrast correction and noise reduction for optimal image preparation. Resizing standardizes image size, reducing computational complexity. Module Specification divides the system into distinct modules for improved

structure. Pre-processing steps like median filtering enhance images for accurate disease diagnosis.

The proposed system, depicted in the circuit diagram (Fig 3.1 b), utilizes the Arduino Uno as the central processing unit, coordinating inputs from various sensors and modules to control outputs effectively. This microcontroller communicates with RFID readers [1], load cells, GPS modules, and IR sensors, executing embedded code to process data and make informed decisions. The Arduino Uno, which serves as the system's controller, makes sure that various components integrate and interact with one another seamlessly for effective herd management.



Fig 3.1 b. Circuit diagram of the designed system

The system comprises essential components such as the power supply unit, LCD display, RFID module, load cell, GPS module, Wi-Fi module ESP8266, motor driver, and motor, providing farmers with comprehensive tools for effective livestock management. These components facilitate accurate cattle registration, health record-keeping, feed weight measurement, movement tracking, internet connectivity for remote monitoring, and automated feeding mechanisms, ultimately empowering datadriven decision-making in sustainable herd management.

### IV. ALGORITHM IMPLEMENTATION

Datasets are sourced from online images and manually categorized into healthy and sick groups, further subdivided by the severity of lumpy skin disease (LSD)[7]. 80% of the data is reserved for model training, with the remaining 20% allocated for testing. A separate section is held out for assessing model performance, ensuring thorough training on a substantial portion of the dataset. This meticulous preparation enables the construction and evaluation of machine learning models capable of distinguishing between healthy and infected cattle, as well as determining LSD [2] severity based on visual cues in the photos.



Fig 4.1 Flow diagram of the disease detection system



Fig 4.2 Architecture of the disease detection system

In image processing, the first step involves converting images to grayscale to capture brightness information, followed by noise removal using techniques like median filtering. Image enhancement techniques refine quality, while segmenting tumor areas in images uses contrast-adjusted black and white images. By measuring the spatial correlations between pixel values, texture patterns are analyzed by feature extraction using GLCM, providing statistical measures aiding tasks like classification and segmentation.



Fig 4.3 Convolutional Layers in Neural Networks

The CNN in Figure 4.3 starts with a 36x36x3 input layer for RGB images. It employs convolutional layers with filters of different sizes, followed by max pooling to reduce spatial dimensions. The first convolutional layer uses nine 11x11 filters, therefore in a 26x26x9 output, followed by max pooling to 12x12x9. The second convolutional layer employs nine 7x7 filters, yielding a 6x6x9 output, further reduced by max pooling to 2x2x9. The output is flattened into a 36-element vector, passed through a fully-connected layer with 6 neurons, and finally to 2 output neurons for prediction. This architecture progressively extracts features represented as convolved matrices (kernels), with each kernel value termed as a weight vector.



Fig 4.4 Matrix image of Convolution Layer

After the convolutional stage in a Convolutional Neural Network (CNN), the next phase involves pooling, where the image matrix is divided into nonoverlapping sets of rectangular segments. Two common pooling techniques are used: Max pooling, which selects the maximum value within each region, and average pooling, which calculates the mean value. The pooling layer enhances computational efficiency and reduces overfitting. The CNN matrix structure is illustrated in Figure 4.4.



Fig 4.5 Structure of CNN in matrix format

The CNN's fully connected layer combines extracted features, forming a vector of 36 numbers from the prior 2x2x9 max pooling layer. This vector passes through six neurons for prediction. Figure 4.5 depicts the system's structure, beginning with acquiring images. Preprocessing methods that lower noise and improve image quality include median filtering and histogram equalization. After segmenting the affected areas, features are recovered using the GLCM algorithm so that CNNs can classify them. This helps doctors choose the right course of treatment depending on the stage of the disease.

# V. RESULTS AND DISCUSSION

An innovative automation solution for cattle livestock involves continuously monitoring feed levels in containers using sensors. When feed levels drop below a set threshold, sensors signal the control unit to activate a dispensing mechanism, releasing the necessary feed amount until the desired level is reached. Alerts are sent to the farmer via a telegram app or computer dashboard if feed levels run low. Each animal is equipped with an RFID tag for precise identification, facilitating efficient management of large herds. Farmers can scan these tags to access comprehensive animal data such as breed, age, vaccination records, and health history stored in a



Fig 5.1 Intimation of the feed



Fig 5.2 RFID reader along with its tag

Each animal is equipped with an RFID tag, providing unique identifier as shown in fig5.2. This allows for precise individual identification, making it easier to manage large herds. Farmers can scan the RFID tag to access detailed information about the animal, including breed, age, vaccination records, and health history. This data is stored in a centralized database, which is easily accessible and updatable and this intimation is given to the farmer in the telegram app.

Real-time location monitoring in a cattle management system involves displaying the geographical coordinates of cattle on an LCD screen, as shown in Figure 5.3.



Fig 5.3 Location coordinates of the cattle

Incorporating GPS technology allows farmers to monitor the real-time location of each animal. This feature is particularly useful for managing free-range cattle that graze over extensive areas. Real time tracking significantly reduces the risk of theft and helps quickly locate stray animals, thereby enhancing the security of the herd.

Lumpy disease[4] is widely seen in cattle. This disease is been detected using Machine Learning

algorithm as shown in fig 5.4a. Fig5.4b shows that the cattle is healthy (stage 0).



Fig 5.4 b The cattle is detected as healthy Stage 1 skin patterns are used to identify animals that have lumpy disease as shown in fig 5.4 c. Fig 5.4 d shows cattle having severe lumpy disease (stage 2).





Fig 5.4 d Stage2 lumpy disease detection

Creating a vaccination reminder system for cattle can significantly improve herd health management by ensuring timely vaccinations. Such a system can be

implemented using various tools and technologies, such as databases, mobile apps, and automated notification systems as shown in fig 5.5 and 5.6



Fig 5.6 The cattle vaccination remainder is set

#### VI. CONCLUSION

In conclusion, the Automation of Cattle Livestock project represents a groundbreaking advancement in rural cattle management, addressing critical challenges such as limited veterinary care, inadequate feeding, and disease outbreaks through the use of advanced technology. This innovative initiative employs an intelligent vaccination scheduler, which creates personalized vaccination plans tailored to the specific needs of individual cattle. By sending timely reminders to owners, this system ensures that vaccinations are administered promptly, thereby preventing the spread of infectious diseases and enhancing overall cattle health. Furthermore, this project empowers farmers by providing them with the tools and knowledge needed to manage their livestock effectively. It fosters a sense of selfsufficiency and confidence among rural farmers, encouraging them to adopt modern practices and technologies. Moreover, the project utilizes advanced image processing techniques to detect early signs of cattle disease. This proactive approach allows for the swift identification and treatment of

health issues before they become severe, significantly reducing mortality rates and improving the quality of livestock. The integration of RFID tags further streamlines the management process by simplifying the registration of new cattle and maintaining accurate health records.

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