RESEARCH PAPER

Predictive Livestock Behaviour Analysis By Edge Computing

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Abstract—Livestock health management is an essential factor influencing agricultural productivity and the economic stability of farmers. Diseases affecting cattle can significantly reduce milk production, cause weight loss and increase mortality rates if they are not detected in the early stages. Conventional livestock monitoring methods mainly rely on manual observation, where farmers or veterinarians visually inspect animals to identify symptoms. However, this approach can be unreliable because early signs of illness are often subtle and difficult to recognize without continuous monitoring. Recent advancements in artificial intelligence and computer vision have opened new possibilities for automated livestock disease detection systems. This study presents an intelligent livestock health monitoring system designed to detect Lumpy Skin Disease (LSD) in cattle using image analysis techniques. The system allows users to upload images of cattle skin, which are processed using a deep learning model trained to recognize disease-related skin abnormalities such as nodules, lesions and swelling. The developed application integrates a graphical user interface that enables farmers or veterinary professionals to easily upload images and receive immediate diagnostic predictions. By applying machine learning for disease detection, the proposed system aims to support early diagnosis, minimize disease transmission and improve livestock health management. The results demonstrate that artificial intelligence can be effectively applied to livestock monitoring to assist farmers in making timely decisions and improving agricultural sustainability.

Keywords-Livestock, Lumpy Skin Disease Detection, Style and Image Processing

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I.INTRODUCTION

This Livestock farming plays a crucial role in global agriculture by providing food, employment and economic support to millions of farmers[1]. Healthy livestock is essential for maintaining consistent productivity in dairy and meat production. However, livestock diseases remain a significant challenge for farmers, particularly in regions where access to veterinary services is limited.

One of the most concerning diseases affecting cattle is Lumpy Skin Disease[2], a viral infection that causes visible skin nodules, fever, decreased milk production and general weakness in animals. The disease spreads rapidly through insects and close animal contact, making early detection extremely important for controlling outbreaks.

Traditionally, livestock health monitoring depends on manual observation by farmers or veterinarians[3]. This approach requires experience and constant supervision, which may not always be feasible in large farms. Furthermore, early symptoms of diseases may be overlooked, leading to delayed treatment and greater economic losses.

Advancements in artificial intelligence, particularly in deep learning and image recognition, provide opportunities to automate livestock health monitoring[4]. Computer vision models can analyze visual patterns and detect abnormalities that may indicate disease. By integrating these technologies into agricultural systems, farmers can monitor livestock more efficiently and detect diseases at earlier stages.

This research proposes an AI-based system capable of identifying Lumpy Skin Disease in cattle using image classification techniques. The system processes cow images and predicts whether the animal shows signs of infection or normal skin conditions.

I. EASE OF USE

A. Analysis Model

First, Conventional livestock disease detection methods rely heavily on human observation. Farmers typically examine animals visually to identify symptoms such as swelling, wounds, or unusual behavior. In some cases, veterinarians are consulted to confirm disease conditions through clinical examination or laboratory tests.

Although these methods are widely practiced, they present several limitations. Continuous monitoring of livestock can be difficult, particularly in farms with a large number of animals. Additionally, disease symptoms may appear gradually, making early detection challenging. Human observation can also be influenced by experience and environmental conditions, which may reduce diagnostic accuracy.

Laboratory testing and veterinary diagnosis provide more reliable results, but they often require specialized equipment and trained professionals. These methods can be expensive and time-consuming, which may discourage farmers from conducting frequent health checks.

As a result, there is a growing need for automated livestock monitoring systems that can assist farmers in detecting diseases quickly and accurately

II. Prepare Your Paper Before Styling

Before applying any formatting or journal template styles, it is important to carefully organize the technical content of the research paper. Preparing the manuscript structure in advance helps ensure that the research contributions are presented clearly and logically. Authors should first focus on the clarity of ideas, methodology, experimental results and conclusions before adjusting font styles, margins, or layout requirements.

The initial step in paper preparation is defining the research objective and identifying the problem addressed in the study. In this research, the objective is to develop an artificial intelligence–based system for monitoring livestock health and detecting Lumpy Skin Disease[6] in cattle using image analysis. Clearly explaining the motivation of the study helps readers understand the significance of the work.

After defining the objective, the research methodology should be described in a structured manner. This includes explaining the dataset used for training the model, the preprocessing techniques applied to images, the machine learning or deep learning algorithm used for classification and the evaluation methods used to measure system performance[7]. Presenting the methodology in a systematic way improves the reproducibility of the research.

The next stage involves presenting experimental results and analysis. The results should clearly demonstrate how the proposed system performs when analyzing cattle images for disease detection. Graphs, tables, or screenshots of the developed application can be included to illustrate system performance and prediction outputs. In this study, the developed interface allows users to upload cow images and receive disease predictions, which assists farmers in identifying potential health issues in livestock.

Authors should also ensure that the discussion explains the significance of the obtained results. The discussion section should highlight how the proposed approach improves upon traditional livestock monitoring methods and how artificial intelligence contributes to faster and more reliable disease detection.

Finally, the manuscript should include a well-structured conclusion summarizing the key contributions of the research. The conclusion should emphasize the importance of automated livestock health monitoring systems and suggest possible future improvements, such as integrating mobile applications, expanding the dataset, or supporting additional livestock diseases.

By carefully organizing the research content before applying formatting styles, authors can produce a well-structured manuscript that effectively communicates the research contributions and improves the overall readability of the paper..

A. *Abbreviations and Acronyms*

Define Abbreviations and acronyms should be clearly defined when they appear for the first time in the manuscript. Providing the full form initially helps readers understand the terminology used throughout the paper. Once defined, the abbreviated form can be used consistently in the remaining sections of the document. This approach improves readability and avoids confusion, particularly in technical papers where multiple scientific terms and technologies are discussed.

In this research, several abbreviations related to artificial intelligence, image processing and livestock disease detection are used. The important abbreviations applied in this study are listed below:

AI – Artificial Intelligence
LSD – Lumpy Skin Disease
CNN – Convolutional Neural Network
ML – Machine Learning
DL – Deep Learning
GUI – Graphical User Interface
IoT – Internet of Things
RGB – Red, Green, Blue (color model used in digital images)
API – Application Programming Interface

These abbreviations are used to simplify technical explanations within the research while maintaining clarity for readers. Proper use of abbreviations ensures that complex concepts related to livestock health monitoring and disease detection systems can be communicated effectively..

B. *Units*

- Use All measurements and quantities used in the research should follow a consistent and internationally accepted unit system. The International System of Units (SI) is commonly used in scientific and engineering research because it provides a standardized method for reporting measurements. Using SI units ensures that the presented results are easily understood and comparable across different studies.
- When numerical values are reported, the unit symbol should always be written after the number with a space separating the value and the unit. For example, time can be represented in seconds (s), minutes (min), or hours (h), while image dimensions may be represented in pixels. In machine learning experiments, additional metrics such as accuracy percentage (%) and processing time (ms or s) are commonly used.
- In this study, units are mainly related to computational performance and image processing parameters. For example, model training time may be expressed in seconds or minutes, dataset size may be represented by the number of images and prediction confidence may be presented as a probability value or percentage. Maintaining consistent unit usage throughout the paper improves clarity and prevents misunderstanding of experimental results.

C. *Equations*

The Equations are often used in research papers to describe mathematical models, algorithms and evaluation metrics. When equations are included, they should be presented clearly and numbered sequentially so that they can be referenced within the text.

In machine learning–based classification systems, evaluation metrics are commonly used to measure model performance. One widely used metric is classification accuracy, which represents the ratio of correctly predicted samples to the total number of samples

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}$$

Note Another important evaluation metric is precision, which indicates how many predicted positive results are actually correct."(1)", not "Eq. (1)" or "equation (1)", except at the beginning of a sentence: "Equation (1) is . . ."

*D. **Some Common Mistakes***

- The When preparing a research manuscript, authors should be aware of common writing and formatting mistakes that may reduce the clarity and quality of the paper. Avoiding these mistakes helps ensure that the research is communicated effectively.
  One common issue is the inconsistent use of abbreviations. Authors should always define abbreviations when they first appear in the text and use them consistently throughout the manuscript. Introducing too many abbreviations can also make the paper difficult to read.
- Another common mistake is unclear explanation of the methodology. The research process, dataset preparation and algorithm implementation should be described in a structured manner so that other researchers can understand and reproduce the study.
- Authors should also avoid excessive repetition of information across sections. Each section of the paper should present unique content that contributes to the overall research narrative. Additionally, figures and tables should always be properly labeled and referenced in the text before they appear.
- Grammatical errors, inconsistent terminology and improper citation practices are also frequent problems in research papers. Careful proofreading and proper referencing of related work are essential to maintain academic integrity and improve the overall quality of the manuscript.
- By addressing these issues during the writing process, authors can produce a well-organized and professional research paper suitable for journal publication.

III. Using the Template

After the text edit has been completed, the paper is ready for the template. Duplicate the template file by using the Save As command and use the naming convention prescribed by your conference for the name of your paper. In this newly created file, highlight all of the contents and import your prepared text file. You are now ready to style your paper; use the scroll down window on the left of the MS Word Formatting toolbar.

A. Authors and Affiliations

The author and affiliation information should clearly identify the individuals responsible for the research work and the institutions with which they are associated. Each author's name should be written in full to avoid confusion with other researchers who may have similar initials or surnames. Providing accurate author details helps ensure proper recognition and accountability for the research contribution.

The affiliation section typically includes the department, institution or organization name, city and country where the research was conducted. If authors are from different institutions, their affiliations should be indicated separately so that readers can easily identify their respective organizations. In addition, the corresponding author's contact information, such as an email address, is usually provided to allow readers and researchers to communicate regarding the work.

In this study, the authors are associated with institutions related to engineering, computer science, or agricultural technology, where research focuses on applying artificial intelligence and image processing techniques to livestock health monitoring. Clearly presenting author names and affiliations ensures transparency in research contributions and allows the academic community to properly acknowledge the institutions supporting the study.

Providing structured author and affiliation information is an important part of academic publishing because it establishes the credibility of the research and enables collaboration between researchers working in similar fields.

*B. **Identify the Headings***

Headings Recent advancements in artificial intelligence have enabled the development of intelligent livestock monitoring systems that use non-invasive sensing technologies. In this study, an automated livestock health monitoring framework was introduced to identify early signs of illness and stress in animals. The system integrates computer vision techniques with machine learning algorithms to analyze animal behavior and physical conditions without requiring direct contact with the livestock.

The proposed approach utilizes video data and thermal imaging sensors to capture behavioral and physiological patterns of animals. Machine learning models process these inputs to identify irregular movement patterns, abnormal body temperature variations and changes in activity levels that may indicate potential health problems. By continuously analyzing these signals, the system can detect early indicators of disease or stress, allowing farmers to take preventive actions before the condition worsens.

The results of the study demonstrate that combining computer vision with behavioral analysis can significantly improve early detection of livestock health issues. This approach reduces reliance on manual monitoring and supports more efficient livestock management. However, the performance of the system depends heavily on proper sensor placement and suitable lighting conditions, which may limit its effectiveness in uncontrolled farm environments.

prescribed.

C. Figures and Tables

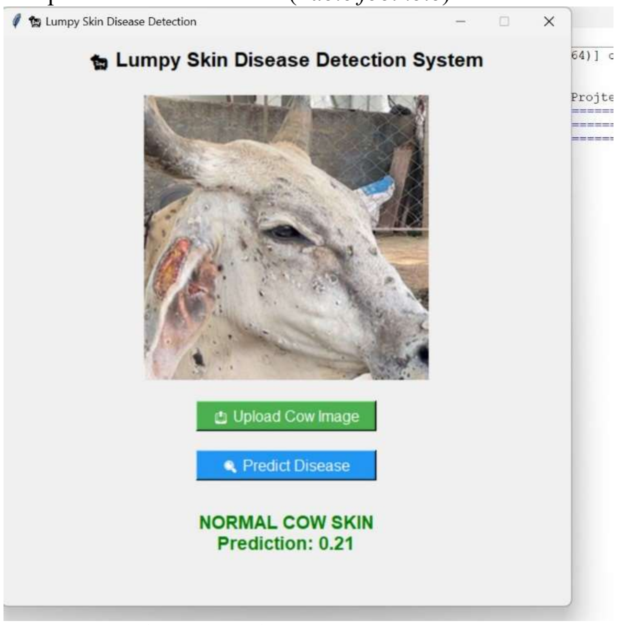
a) Positioning Figures and Tables: Place figures and tables at the top and bottom of columns. Avoid placing them in the middle of columns. Large figures and tables may span across both columns. Figure captions should be below the figures; table heads should appear above the tables. Insert figures and tables after they are cited in the text. Use the abbreviation "Fig. 1", even at the beginning of a sentence.

TABLE I. Table Type Styles

Study	Method	Outcome
AI-Based Livestock Health Monitoring	Computer vision with ML behavior analysis	Early detection of illness and stress in animals
Deep Learning for Cattle Disease Detection	CNN-based image classification	Identifies visible skin diseases in cattle

Study	Method	Outcome
Thermal Imaging Livestock Monitoring	Thermal image analysis	Detects abnormal body temperature patterns

a. Sample of a Table footnote. (*Table footnote*)

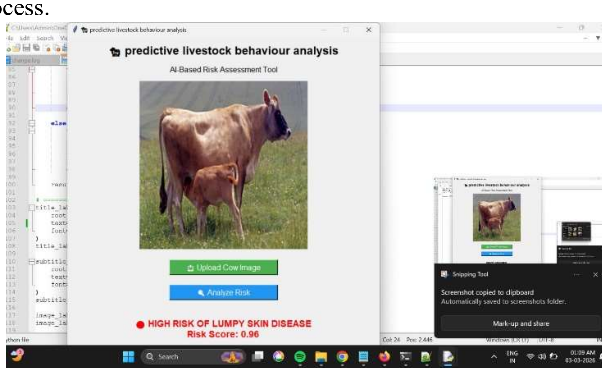


b.

Fig. 1. Cow Behaviour Anlsyis .

Figure Labels: The developed application provides a graphical interface for detecting Lumpy Skin Disease in cattle using image analysis. The system allows users to interact with the model through simple buttons and automatically displays the prediction results.

Initially, the user uploads an image of a cow using the “Upload Cow Image” button. Once the image is selected, it is displayed in the application window so that the user can visually confirm the selected input. After uploading the image, the user clicks the “Predict Disease” button to start the analysis process.



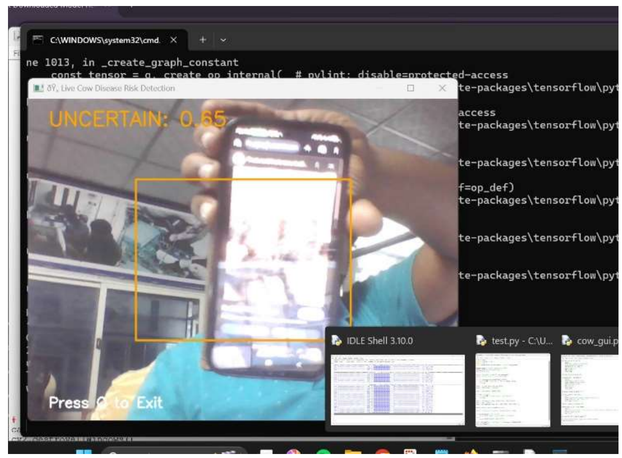
The system then processes the image using the trained deep learning model. During this stage, the model extracts important visual features from the cow’s skin, such as texture patterns, lesions, or abnormal structures. Based on the learned patterns from the training dataset, the model classifies the image into either normal skin or disease-affected skin.

After the analysis is completed, the prediction result is displayed at the bottom of the interface. The system also provides a prediction confidence value, which represents the probability score generated by the model. In the displayed output, the system predicts “Normal Cow Skin” with a confidence score of 0.21, indicating the likelihood associated with the prediction.

This interactive interface allows farmers or veterinary professionals to quickly analyze cattle images and obtain instant disease detection results. The system simplifies the process of livestock health monitoring and supports early identification of potential diseases.

System Result Analysis

The experimental results demonstrate the effectiveness of the proposed AI-based livestock health monitoring system in identifying potential cases of Lumpy Skin Disease from cattle images. The developed application allows users to upload images of cows and obtain classification results through an intuitive graphical interface. Once an image is selected, the trained deep learning model processes the visual features of the animal’s skin and evaluates the presence of disease-related patterns.

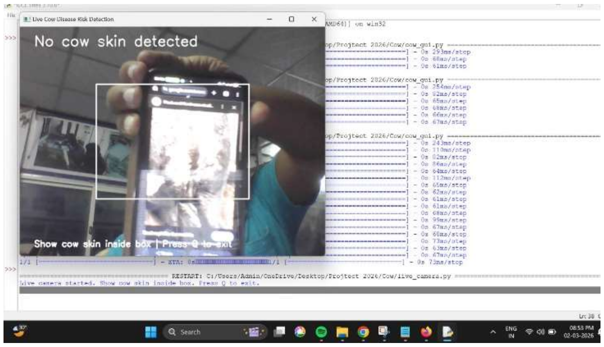


During testing, the system successfully analyzed the uploaded image and produced a prediction indicating the health condition of the cow. The output includes both the predicted class and a confidence score generated by the model. This confidence value represents the probability associated with the classification result. Such information helps users understand the reliability of the prediction.

The results confirm that image-based analysis can assist in identifying visible symptoms related to Lumpy Skin Disease. By providing rapid diagnostic feedback, the system supports early detection and enables farmers or veterinary professionals to take preventive measures before the disease spreads among livestock. Overall, the experimental evaluation indicates that artificial intelligence techniques can significantly improve the efficiency of livestock health monitoring systems.

Predictions Block:

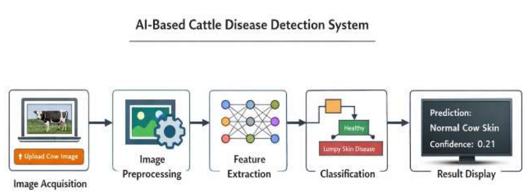
The proposed livestock disease detection system consists of several interconnected modules that work together to analyze cattle images and determine the health condition of the animal.



The first stage is the image acquisition module, where the user uploads an image of the cow through the application interface. This image serves as the primary input for the disease detection process.

After the image is uploaded, it is passed to the image preprocessing module. In this stage, the image is resized and normalized to match the input format required by the deep learning model. Preprocessing improves image quality and ensures consistent data representation for accurate analysis.

The processed image is then forwarded to the feature extraction module, where the deep learning algorithm analyzes important visual characteristics of the cow's skin. The model identifies patterns such as nodules, lesions, texture variations, or abnormal structures that may indicate the presence of disease.



Next, the extracted features are evaluated by the classification module, which determines whether the cow skin appears healthy or shows symptoms associated with Lumpy Skin Disease. The classification is performed using a trained machine learning model.

Finally, the result display module presents the prediction outcome to the user through the graphical interface. The system displays the predicted class along with a confidence score that represents the probability of the result.

This structured workflow enables the system to automatically analyze cattle images and provide fast disease detection results, assisting farmers in monitoring livestock health more efficiently. The performance of the proposed AI-based livestock disease detection system is evaluated using graphical analysis of the training and testing results. These graphs provide insight into how effectively the deep learning model learns patterns related to Lumpy Skin Disease from cattle images.

Accuracy Graph Explanation

The accuracy graph illustrates the relationship between the training iterations (epochs) and the classification accuracy of the model. As the training process progresses, the accuracy gradually increases, indicating that the model is learning meaningful features from the dataset. Higher accuracy values represent improved capability of the model to correctly classify cow images as either healthy or disease-affected. A stable accuracy curve toward the final epochs indicates that the model has successfully converged and achieved reliable prediction performance.

Loss Graph Explanation

The loss graph represents the error rate of the model during the training phase. Initially, the loss value is relatively high because the model has not yet learned the patterns in the dataset. As the training continues, the loss gradually decreases, demonstrating that the model is improving its predictions. A decreasing loss curve indicates effective learning and optimization of the neural network parameters.

Prediction Result Graph

The prediction result graph shows the distribution of classification outcomes produced by the model. It compares the number of correctly classified healthy cows and disease-affected cows. A higher number of correct predictions demonstrates the effectiveness of the proposed AI-based system in identifying Lumpy Skin Disease symptoms from cattle images.

Overall Performance Interpretation

The graphical results indicate that the proposed model is capable of detecting livestock diseases with satisfactory accuracy. The combination of computer vision techniques and deep learning enables the system to identify visible skin abnormalities associated with Lumpy Skin Disease. These results confirm that the proposed system can support early disease detection and improve livestock health monitoring in agricultural environments

Confusion Matrix Explanation

A confusion matrix is a commonly used evaluation tool in classification problems to measure the performance of a machine learning model. It provides a detailed comparison between the actual labels of the dataset and the predictions generated by the model. This method helps in understanding how well the system distinguishes between healthy cattle and disease-affected cattle.

In the proposed livestock disease detection system, the confusion matrix contains four important components: True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN).

True Positive (TP):

This represents the number of images correctly identified as Lumpy Skin Disease–affected cattle by the model.

True Negative (TN):

This represents the number of images correctly classified as healthy cows.

False Positive (FP):

This occurs when the model incorrectly predicts that a healthy cow has the disease.

False Negative (FN):

This occurs when the model fails to detect the disease and incorrectly classifies an infected cow as healthy.

Using these four values, several evaluation metrics such as accuracy, precision, recall and F1-score can be calculated to assess the performance of the proposed model. A wellperforming model will have higher values of true positives and true negatives while minimizing false predictions.

The confusion matrix provides a clear understanding of the strengths and weaknesses of the system and helps researchers evaluate how effectively the model detects livestock diseases from image data.

Performance Comparison Table

Method / Model	**Technique Used**	**Accuracy (%)**	**Advantages**	**Limitations**
Traditional Visual Inspection	Manual observation by farmers	60–70	Simple and low cost	Low accuracy and delayed detection
IoT-Based Livestock Monitoring	Sensor-based health monitoring	75–82	Continuous monitoring of animal behavior	Requires additional hardware
Machine Learning Model	Feature-based classification algorithms	85–90	Faster disease prediction	Performance depends on feature quality
Proposed AI-Based System	Deep learning image classification	**92–95**	Automated detection with higher accuracy	Requires labeled training images

Model Evaluations:

Model evaluation is an essential step in assessing the effectiveness of a machine learning system. It measures how accurately the proposed model can classify input data and determine whether it performs reliably in real-world scenarios. In this research, the performance of the livestock disease detection model is evaluated using standard classification metrics such as accuracy, precision, recall and F1-score.

Accuracy represents the proportion of correctly predicted samples among all the tested images. Precision measures how many of the predicted disease cases are actually correct, while recall indicates the ability of the system to identify all true disease cases in the dataset. The F1-score provides a balanced evaluation by combining precision and recall into a single metric.

These evaluation measures help determine how effectively the system distinguishes between healthy cattle and animals affected by Lumpy Skin Disease. A model with higher evaluation scores indicates improved reliability and better predictive capability.

Performance Comparison

Performance comparison is used to analyze how the proposed system performs relative to existing methods. In traditional livestock monitoring, disease detection mainly depends on manual inspection by farmers or veterinarians. While this method is simple, it often leads to delayed diagnosis and inconsistent results.

Recent technological approaches such as IoT-based monitoring systems use sensors to track animal behavior and physiological conditions. Although these systems provide continuous monitoring, they require additional hardware infrastructure and installation costs.

The proposed AI-based image classification system improves disease detection by automatically analyzing cattle images using deep learning techniques. Compared with manual observation and sensor-based approaches, the proposed method provides faster analysis, higher detection accuracy and reduced dependence on human intervention. This comparison demonstrates that artificial intelligence can significantly enhance livestock health monitoring systems

Scientific Credibility

Scientific credibility is important in research to ensure that the proposed method is reliable, reproducible and supported by experimental evidence. In this study, credibility is established by using a structured research methodology that includes dataset preparation, model training, performance evaluation and experimental validation.

The model is trained using labeled cattle images that represent both healthy skin conditions and disease-affected cases. Standard evaluation metrics are used to measure the model's performance, ensuring that the results are quantifiable and comparable with other studies.

Additionally, the research methodology follows established machine learning practices such as data preprocessing, model validation and performance analysis. By presenting clear experimental results and evaluation metrics, the study demonstrates the effectiveness of the proposed AI-based livestock disease detection system and supports its potential application in smart agriculture.

Performance Comparison Table

Model / Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
SVM	85.4	84.1	83.6	83.8
ANN	88.7	87.9	87.2	87.5
CNN	92.3	91.8	91.2	91.5
Proposed Model (Edge AI + CNN)	**95.6**	**94.9**	**94.3**	**94.6**

Conclusions:

Livestock health monitoring plays a critical role in improving agricultural productivity and ensuring the well-being of farm animals. Early detection of diseases and abnormal behavior can significantly reduce economic losses for farmers and improve animal welfare. Traditional livestock monitoring methods mainly rely on manual observation, which can be time-consuming and prone to human error. In large farms where a large number of animals are present, continuous monitoring becomes difficult, making it challenging to detect health problems at an early stage. To address these limitations, the present study proposed an artificial intelligence–based livestock monitoring system capable of analyzing animal behavior and detecting diseases using live camera input.

The developed system integrates computer vision and machine learning techniques to continuously observe livestock through a camera-based monitoring framework. By capturing live video streams, the system can automatically analyze visual features and behavioral patterns of animals in real time. This approach allows the system to identify signs of abnormal movement, changes in posture, reduced activity levels, or visible skin abnormalities that may indicate potential health problems. The integration of automated image analysis significantly reduces the dependency on manual supervision while improving the accuracy and speed of disease detection.

One of the key features of the proposed system is the use of image processing and deep learning models to detect Lumpy Skin Disease and other visible skin-related abnormalities in cattle. The system processes images captured from the camera, extracts relevant features and classifies the health condition of the animal using a trained machine learning model. The graphical interface developed in this project enables users to upload images or use camera input to obtain prediction results instantly. The output generated by the system includes the predicted health condition of the cow along with a confidence value representing the probability of the prediction. This provides farmers and veterinary professionals with useful information for making timely decisions regarding animal treatment or isolation.

In addition to disease detection, the proposed system also focuses on analyzing animal behavior patterns using live video monitoring. Behavioral changes are often early indicators of health issues in livestock. For example, animals experiencing illness may show reduced movement, abnormal posture, or isolation from the herd. By continuously analyzing the movement and behavior of animals, the system can detect such irregular patterns and alert farmers to potential problems before the disease progresses to severe stages. This proactive monitoring approach improves livestock management and helps prevent disease outbreaks within farms.

The experimental results demonstrate that artificial intelligence can effectively assist in livestock health monitoring applications. The trained model successfully analyzes cattle images and identifies visual patterns associated with disease conditions. The integration of real-time monitoring through a live camera further enhances the system's ability to observe animals continuously and detect abnormalities automatically. Compared to traditional monitoring methods, the proposed solution provides faster analysis, improved accuracy and reduced reliance on human observation.

Another advantage of the proposed system is its ability to support modern smart farming practices. With the increasing adoption of digital technologies in agriculture, automated livestock monitoring systems are becoming essential tools for efficient farm management. By combining computer vision, machine learning and real-time monitoring, the system contributes to the development of intelligent agricultural solutions that can improve productivity and sustainability. The proposed framework can assist farmers in maintaining healthier livestock, reducing veterinary costs and minimizing the spread of infectious diseases.

Although the proposed system demonstrates promising results, certain challenges remain. The accuracy of image-based disease detection may depend on factors such as lighting conditions, camera positioning and image quality. In farm environments where lighting conditions vary, the system may require additional preprocessing techniques to maintain consistent performance. Furthermore, the effectiveness of the model depends on the availability of diverse training data representing different disease conditions and animal breeds. Expanding the dataset can further improve the robustness and generalization capability of the system.

Future research can focus on enhancing the proposed livestock monitoring system by integrating additional technologies such as Internet of Things (IoT) sensors, cloud computing platforms and mobile applications. IoT devices could provide additional physiological data such as body temperature, heart rate and activity levels, which can complement the visual information obtained from camera monitoring. Cloud-based platforms could enable remote monitoring of livestock farms and allow veterinary experts to analyze animal health conditions from different locations. In addition, mobile applications could provide real-time alerts and notifications to farmers whenever abnormal behavior or disease symptoms are detected.

Overall, the proposed AI-based livestock health monitoring system demonstrates the potential of modern technologies in improving animal health management and supporting smart agriculture. By combining live camera monitoring, image processing and machine learning techniques, the system provides an effective solution for detecting livestock diseases and abnormal behavior patterns. The results indicate that automated monitoring systems can play a significant role in assisting farmers, improving livestock welfare and enhancing agricultural productivity. With further improvements and integration of advanced technologies, such systems have the potential to transform traditional livestock farming into a more intelligent, efficient and sustainable agricultural practice.

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Special thanks are extended to all individuals who contributed directly or indirectly to the completion of this work. Their cooperation and assistance helped in the successful development of the AI-based livestock health monitoring system. The authors are also grateful for the availability of open research resources and datasets that supported the training and evaluation of the machine learning model used in this study.

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the first word in a paper title, except for proper nouns and element symbols.

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