# DEVELOPMENT OF AN AI-POWERED WEB-BASED CATTLE LAMENESS DETECTION SYSTEM

**BY**

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**A PROJECT SUBMITTED TO**
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## APPROVAL PAGE

This research, titled "DEVELOPMENT OF AN AI-POWERED WEB-BASED CATTLE LAMENESS DETECTION SYSTEM," has been assessed and approved by the Department of Computer Science and Mathematics Committee in the Faculty of Computing and Information Technology, Godfrey Okoye University, Enugu, Nigeria.

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## CERTIFICATION

I certify that I completed the research included herein and that it was primarily based on my observations and investigation. Consequently, I will fully accept the University's decision if I am found to have engaged in academic misconduct.

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# DEDICATION

This project is dedicated to the glory of God Almighty, the Maker of heaven and earth, to whom all honour and adoration are due, the Author and Finisher of my faith. It is also dedicated to my parents, Mr. and Mrs. Uchegbu, who laid the foundation of my success, and to my caring brothers and sisters for their love and unwavering support throughout this journey.

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## ABSTRACT

Lameness in cattle is one of the main problems for both dairy and beef farming since it causes decreased milk yield, reduced fertility rate, increased costs for veterinary services, and premature slaughtering. Detecting the problem is hard even on some farms due to the subjective nature of visual assessments used to detect lameness. Therefore, this paper presents the results of the development of an internet-based automated cattle lameness detection system based on video analysis using computer vision techniques and machine learning algorithms. To detect and track cattle in video images, this system employs a pre-trained YOLOv8 model. The system identifies several gait parameters such as movement velocity, stride displacement, straightness of the path, lateral swaying, bounding box variation ratio, vertical oscillations, stride regularity, and lateral imbalance, which serve as input values for the machine learning model. An SVM model trained using 50 freely accessible cattle videos split into 80% training and 20% testing samples scored an accuracy of 70%. The output from the classifier showed that the classes have asymmetric performance, where the lame class has a precision of 0.75, a recall of 0.60, and an F1 score of 0.67 while the normal class has a precision of 0.67, a recall of 0.80, and an F1 score of 0.73. The F1 score generated for the classes resulted in a macro-average F1 score of 0.70. Therefore, the system was capable of recognizing gait differences but still needs more improvement to be able to consistently predict lame instances. The application was implemented using Flask technology, allowing users to automatically input cattle videos into the system for lameness diagnosis along with the probability of lameness in form of severity. This study showed that it is feasible to use gait analysis through videos as a cheap decision-support tool in diagnosing lameness cases. Since the model was trained using a limited dataset, future research should aim at improving the system by training it using a diverse dataset in terms of breeds, cameras used, environment, and lameness severity.

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# CHAPTER ONE

# INTRODUCTION

## 1.1 Background of the Study

Livestock production contributes significantly to the economies of many countries around the world, especially the developing ones where agriculture remains the mainstay. This sector employs millions of people, and it is estimated that the total number of individuals whose livelihood is derived from livestock production amounts to about 1.3 billion people globally (Herrero et al., 2020). In relation to other livestock, cattle remain important for agricultural activities across the globe as they serve various purposes, such as meat supply, dairy products, draught power, and economic gain for both subsistence and commercial farmers.

Even though livestock play an important role in economies and food supplies, they suffer from various diseases, which affect not only the productivity of the animals but also their overall wellbeing. Of particular significance amongst various diseases, the one that affects cattle is lameness. It refers to any hindrance in the normal locomotory capacity of the animals, which may be related to pain or other defects in the feet or limbs (Qiao et al., 2021). This disease is regarded as one of the costliest diseases affecting the dairy and beef sectors due to its effects on milk output, breeding, veterinary care, among others.

There have been multiple studies demonstrating the presence of objective gaits changes in lameness cases, such as decreased walking velocity, decreased step length, uneven weight bearing, and typical arching of the back (Kang et al., 2025). For instance, in dairy cows, it has been estimated that between 15% and 35% of cows suffer from lameness (O'Leary et al., 2020). These numbers clearly show the importance of this issue as a persistent welfare problem for the livestock industry. Moreover, since lameness is associated with pain, affected animals often struggle to reach food and drink sources, lack opportunities to behave normally, and are more likely to develop other diseases as well.

Traditionally, the problem has been addressed using locomotion scoring methods, where specially trained personnel assess the gait of animals using ordinal scoring systems. These techniques allow for consistent evaluation of the gait of cattle. However, due to their subjectivity and relatively long duration of assessments, they tend to be quite unreliable. At the same time, the issue can be further complicated by the need to have properly trained personnel on hand, which is not always feasible in intensive commercial farms (Gardenier et al., 2021).

The development of artificial intelligence (AI), computer vision, and machine learning techniques has provided opportunities for the development of automation and objective techniques of monitoring cattle health status. Some researchers have successfully applied AI, computer vision, sensors, and machine learning to lameness detection with various levels of accuracy, including 98% or above, while manual scoring is subjective and inaccurate (Wu et al., 2020; Myint et al., 2024; Sohan et al., 2026). The systems detect subtle patterns of movements in cattle, which cannot be reliably detected by humans, especially at an early stage of lameness.

In Nigeria and other countries of sub-Saharan Africa, farmers that breed cattle in a small scale have further limitations compared to their counterparts who use their farms for commercial purposes. The automated lameness detection technologies currently developed require costly hardware and installation procedures, which are too expensive for farmers in underdeveloped countries to afford. Therefore, in this research, an automatic web-based system for detecting lameness in cattle based on motion analysis in the video was developed. It can be accessed through a web browser on the basis of uploaded videos recorded using a regular smartphone without any special equipment.

### 1.2 Statement of the Problem

1. Livestock farmers, including cattle keepers in both developed and developing regions, largely depend on physical and visual inspection to identify health problems in their animals. However, early-stage lameness typically presents through subtle gait changes that are difficult to detect through casual observation, particularly in large herds where individual attention to each animal is limited. As a consequence, lameness is frequently identified only when it has progressed to a severity at which the animal exhibits obvious limping or postural distortion, resulting in deterioration of animal health, escalated treatment costs, and in the most severe cases, permanent injury or premature loss of the animal.
2. The associated impacts on feeding behaviour, growth rate, milk production, and reproductive performance result in substantial economic losses for farmers. These challenges are particularly acute among smallholder farmers who lack access to automated monitoring technologies and affordable veterinary diagnostic services. Manual scoring is inconsistent, labour-intensive, and unavailable to rural farmers without veterinary support — and can detect as few as 20–35% of clinically lame cattle through routine observation (Gardenier et al., 2021).
3. At present, existing automated lameness detection systems require expensive fixed-camera installations, specialised sensor hardware, or large computational infrastructure, making them economically inaccessible to smallholder and subsistence farmers, particularly in developing regions such as Nigeria and sub-Saharan Africa. There is therefore a notable absence of simple,

accessible digital platforms that allow farmers to upload cattle movement videos recorded on ordinary smartphones, receive automated lameness classification results, and maintain a searchable history of detection records over time. This study addresses this gap by developing a practical, affordable, and automated web-based AI solution for early detection of lameness and improved livestock health management.

### 1.3 Aim and Objectives of the Study

The aim of this study is to develop an AI-powered web-based cattle lameness detection system.

To achieve the stated aim, the following specific objectives were pursued:

1. Investigate existing methods of lameness detection in cattle and identify their limitations.
2. Design an AI-powered cattle lameness detection system based on video-based gait analysis.
3. Implement the system as a web-based application.
4. Evaluate the performance of the AI-powered cattle lameness detection system.

Develop the approach into a real system that detects lameness in cattle based on video-based gait analysis

### 1.4 Significance of the Study

This research is important from several angles. Cattle farmers will get an effective tool, which does not cost too much money and allows recognizing problems like lameness at their earlier stage and, therefore, applying necessary measures on time before the situation aggravates. It may help avoid unnecessary expenses associated with veterinarian services and potential losses caused by serious cases of lameness.

For veterinarians, this system can be an effective auxiliary means. Video evidence and the ability to review movement history allow giving a more professional diagnosis and track the effectiveness of treatment throughout some time. The web-based version of the platform can be used easily without having any special equipment other than a regular laptop connected to the Internet.

Sectorally speaking, such monitoring systems can improve animal welfare, contribute to productivity sustainability, and enhance food security of developing countries. Moreover, the findings of this research will provide an important addition to the body of academic knowledge devoted to the applications of AI and computer vision techniques in agriculture.

### 1.5 Scope of the Study

In the present paper, attention was paid to the detection of the state of lameness in cattle based on the analysis of the short video clips depicting individual animal movements. The web-based application designed to detect signs of lameness allowed uploading video files in the format of .mp4, .avi, .mov, and .mkv, receiving the output in form of automated classification (Normal/Suspected Lameness), as well as accessing historical information. The methodology adopted to perform the detection involved extraction of the set of motion features, along with their classification by means of SVM.

The project only considered the analysis of short videos depicting cattle moving under normal farm conditions and utilizing consumer-level video equipment. The dataset employed was the public Cattle Lameness Dataset (Sohan et al., 2026) and consisted of 50 labeled videos. As external variables not covered in this research project include complicated medical conditions, laboratory tests, live video feed, and data collected via sensors. It should be emphasized that the described system is to function as a support tool for veterinarians and farmers but not replace professional examination. To develop the front-end side, HTML5, CSS3, and JavaScript were used. For the back-end development, the choice fell on Flask/Python.

**1.6 Limitations of the Study**

However, the accuracy of the system also depends on the quality of the uploaded videos and on proper camera positioning at the time of recording, since poor lighting conditions, low-resolution images, or camera obstruction can negatively affect the accuracy of features identification and, therefore, lameness classification.

The video database, consisting of 50 short videos, was used in order to train and test the system, which is adequate for the purpose of a prototype; however, such sample size is not enough for a model capable of working with different breeds of cattle, in various farm environments, and different degrees of lameness. The current prototype supports on-demand uploads only, and does not work with live cameras and continuous recording and does not require a GPU, although the processing speed on a normal CPU would be slower. Moreover, wearable sensors are currently unsupported by the system. There are no individual cattle profiles; only video and video analytics are stored.

**1.7 Operational Definition of Terms**

1. Lameness: A physical condition in cattle characterised by abnormal locomotion, gait irregularities, or impaired weight-bearing in one or more limbs, typically associated with pain or structural dysfunction.
2. Gait Analysis: The systematic study of animal locomotion, involving the measurement and assessment of movement parameters such as stride length, walking speed, and limb symmetry to evaluate health and mobility.

3. Pose Estimation: A computer vision technique that identifies and tracks the positions of anatomical keypoints (joints or body landmarks) within an image or video frame to reconstruct the posture of an animal or person.
4. YOLOv8: The eighth iteration of the You Only Look Once (YOLO) family of real-time object detection and pose estimation algorithms, known for high speed and accuracy in identifying and localising objects within images and video.
5. Bounding Box: A rectangular region drawn around a detected object in an image or video frame, used to indicate its location and extent within the scene.
6. Lameness Score: A numerical or categorical rating assigned to an animal's gait quality, typically on an ordinal scale, indicating the perceived degree of locomotion impairment.
7. Precision Livestock Farming: An approach to animal husbandry that applies digital technologies, sensors, and data analytics to monitor individual animal health, behaviour, and productivity at a granular level.
8. Web-Based System: A software application delivered and accessed through a web browser over the internet, requiring no dedicated client-side installation beyond a standard browser.
9. REST API: Representational State Transfer Application Programming Interface; a set of architectural principles for building web services that allow communication between a frontend client and a backend server using standard HTTP methods.
10. JWT Authentication: JSON Web Token authentication; a stateless mechanism for securely transmitting identity information between client and server using digitally signed tokens.
11. Flask: A lightweight Python web framework used for building backend REST APIs and web applications.
12. React: A JavaScript library for building component-based, reactive user interfaces for web applications.
13. SQLite/PostgreSQL: Relational database management systems; SQLite is a file-based, serverless database suitable for development and small-scale deployment, while PostgreSQL is a full-featured server-based system suitable for production.
14. Recording: In the context of this system, a video file uploaded by a user for lameness analysis, together with its associated metadata and analysis result.
15. DetectedAnimal: A database entity representing a specific animal identified within an uploaded video recording, linked to its corresponding analysis result and lameness classification.

# CHAPTER TWO

# LITERATURE REVIEW

## 2.1 Introduction

The current chapter provides an in-depth review of the existing body of literature on the topic of cattle lameness detection through artificial intelligence. The objective of the literature review presented herein is to provide insight into the background of research done on the topic and to provide justification for the significance of current research by analyzing achievements made in the field thus far as well as the remaining gaps. By critically analyzing the scholarly articles, research papers, and technical reports available on the topic from 2020 to 2026, strengths and weaknesses of current methods will be identified, thus forming the basis of the current study.

## 2.2 Theoretical Background

### 2.2.1 Cattle Lameness: Nature, Prevalence, and Economic Impact

Lameness in dairy and beef cattle is any abnormality in locomotion and gait that suggests an impairment or painful state in the musculoskeletal system, especially in legs and feet. Lameness is one of the most economically devastating diseases on dairy farms besides mastitis and reproductive conditions (Qiao et al., 2021). Worldwide, the prevalence rates of lameness among dairy cows range from 15% to 36% with considerable variations depending on the animal husbandry systems, housing types, flooring materials, and nutrition (O'Leary et al., 2020).

In cattle, the clinical causes of lameness are mainly categorized into infectious and non-infectious hoof problems. The former are mostly footrot and digital dermatitis, while the latter are sole ulcer, white line disease, and horn disruption. These infections impair the physical condition of hooves leading to changes in gait such as back arching, shortened stride, decreased walking speed, and uneven weight bearing. At an early stage, lameness occurs subtly making it difficult to diagnose without automation.

The effects of lameness on economies are complex. The animals suffering from this condition tend to produce less milk, their reproductive capacity is hindered, they lie down for extended periods, and they face the danger of being culled early. This means that lameness causes financial losses and also contributes to broader problems in the production of cattle. In underdeveloped countries like Nigeria, the effect of lameness can be quite profound.

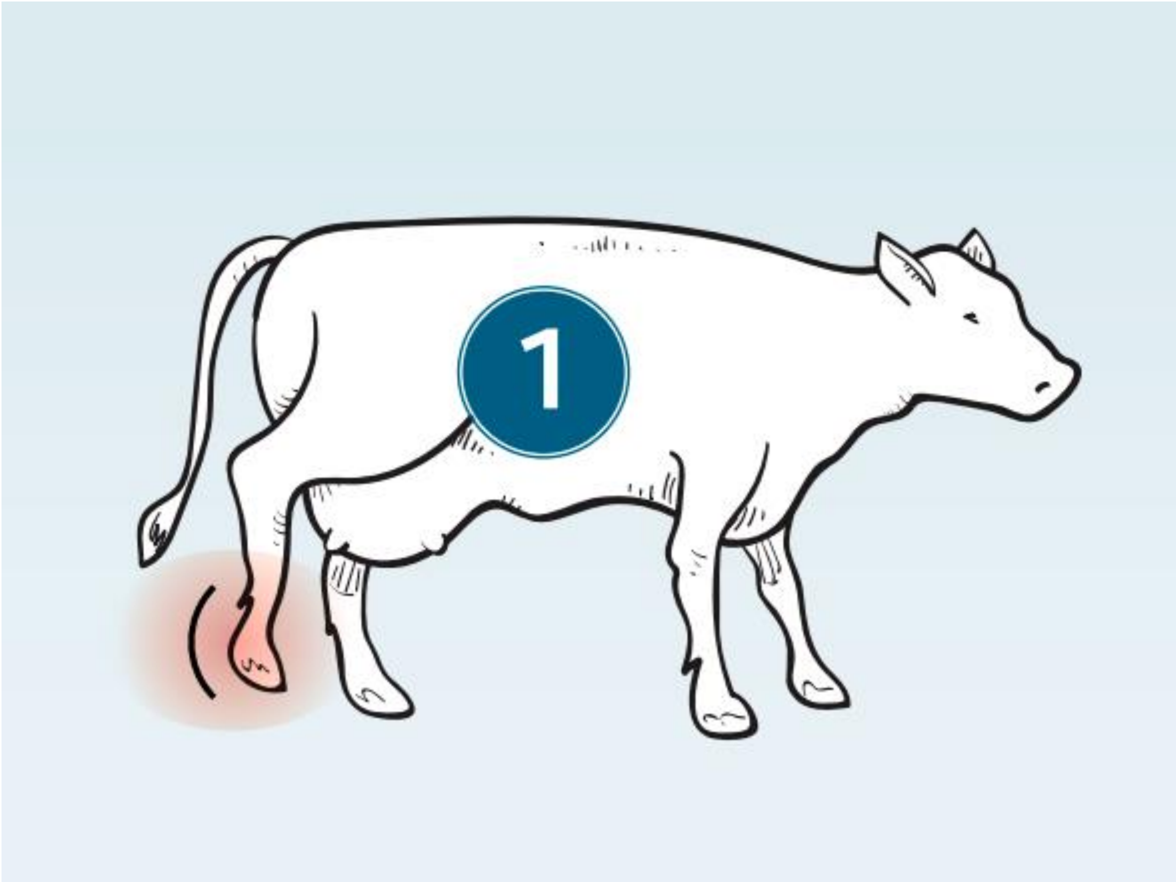


**Figure 2.1: Visual Representation of a Lame Cow Showing Characteristic Back Arch**

### 2.2.2 Conventional Methods of Lameness Detection

The traditional method for lameness detection in cattle entails Manual Locomotion Scoring (MLS), where trained persons observe individual animals' locomotive pattern and give score on an ordinal scale system. Several scoring systems have been adopted with the most popular being the five-point scoring system developed by Sprecher et al. and its subsequent modification. This method looks at various gait attributes such as stride length, stride regularity, body weight distribution, and back posture while walking.

Nevertheless, manual scoring methods face numerous challenges. Firstly, they are observer-based hence prone to bias due to high levels of subjectivity, making results vary with different observers over time and thus cannot be used reliably in large herd management (Gardenier et al., 2021). Secondly, the system is costly to implement since it is laborious and cannot be used for real-time monitoring purposes. Research studies have indicated that manual scoring systems detect only 20%-35% of clinically lame cattle. Wearable accelerometer and pressure plate systems provide accurate results but are relatively costly to acquire.

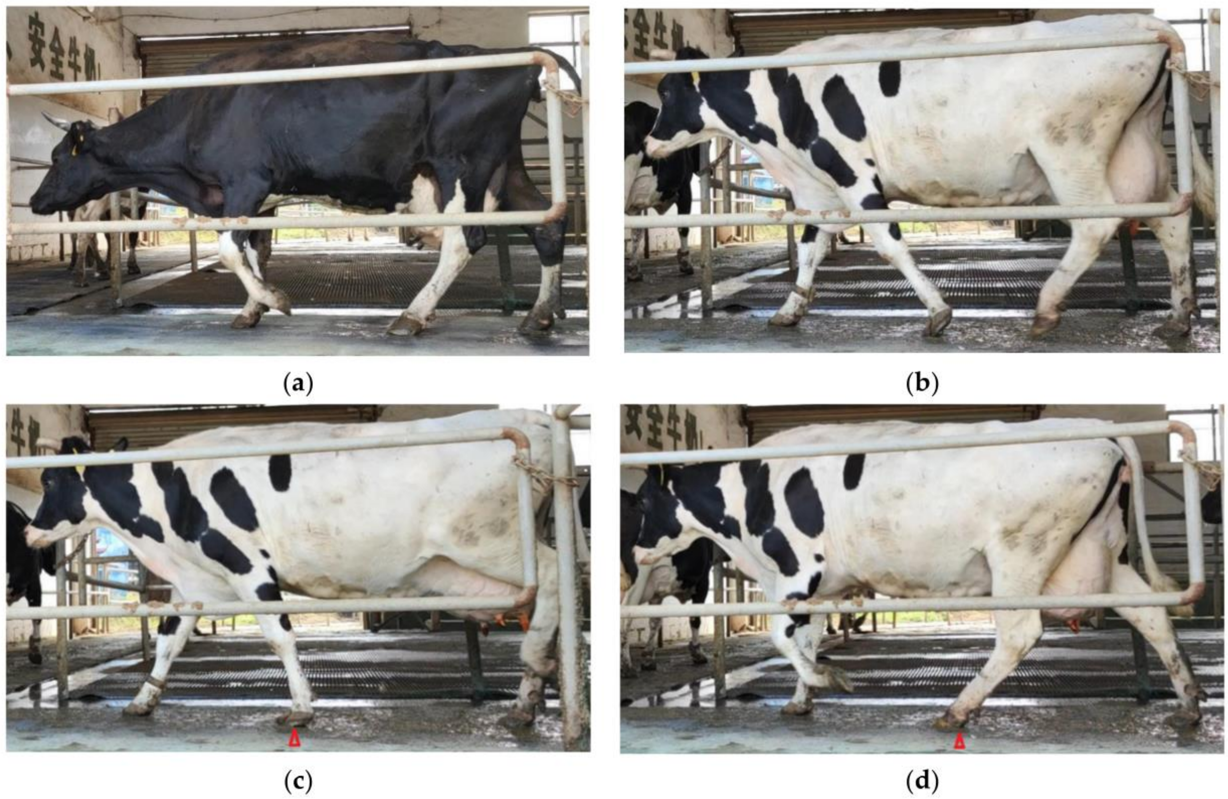


**Figure 2.2: Comparison of Lame and Non-Lame Cow Postures — Gait and Postural Differences**

### 2.2.3 Computer Vision and AI Techniques for Lameness Detection

Approaches to automatic lameness detection are generally classified according to kinetic, kinematic, and indirect methods. Kinetic approaches assess the forces related to locomotion such as ground reaction forces. Kinematics evaluates the path, location, and velocities of body parts in movement. On the other hand, indirect approaches detect behavioral and production parameters, for example, the amount of time spent lying, which could be used to infer lameness (Qiao et al., 2021).

Computer vision systems use the visual data obtained from the 2D or 3D video/images to detect the gait abnormalities due to lameness. The 2D systems tend to be inexpensive yet lacking depth information compared to 3D systems that have better spatial resolution but require high-cost equipment. Some feature extraction algorithms used by the computer vision system for lameness detection include background subtraction, optical flow, keypoint detection, and deep learning-based object detection methods, especially the You Only Look Once (YOLO) family like YOLOv3 and YOLOv8.

The deep learning approaches like Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) have shown remarkable accuracy when used to classify lameness problems. The CNN network has been proven efficient in extracting the spatial characteristics of the image data, while LSTM is adept in capturing the time-dependent nature of video data (Wu et al., 2020). The combination of both networks has delivered results above 90% detection accuracy.

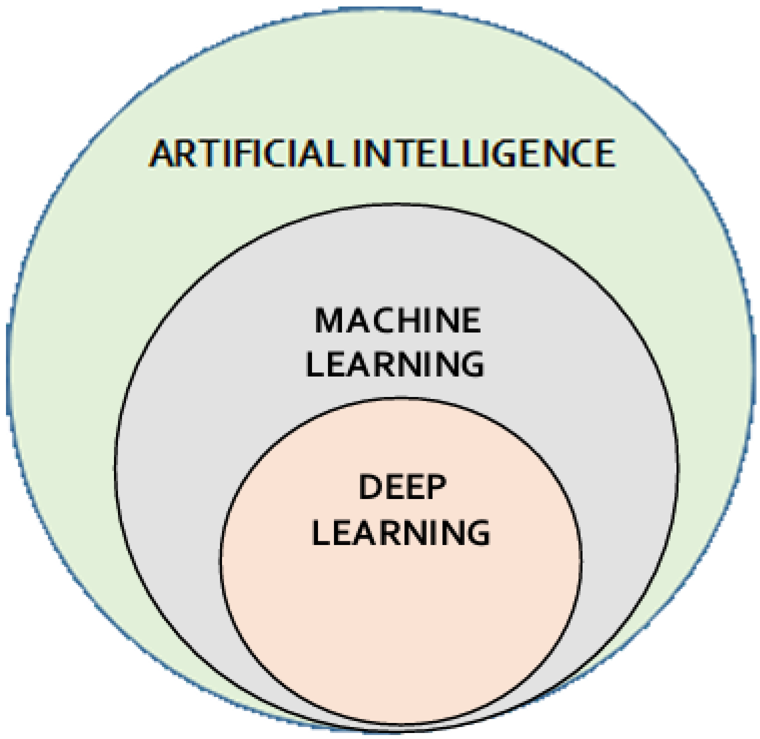


**Figure 2.3: Subsets of Artificial Intelligence — Machine Learning and Deep Learning Hierarchy**

### 2.2.4 Machine Learning Theory and Application

Machine Learning refers to the branch of artificial intelligence whose focus is on creating intelligent algorithms through data pattern recognition and using this information to perform actions such as predictions and classifications on other data samples. The supervised machine learning approach involves learning through labeled datasets where there are both input and output variables. When used in detecting lameness in cattle, the inputs can be the motion parameters extracted from the video frame while the output will indicate either lame or not lame.

The most common supervised machine learning algorithms used in analyzing livestock health status are Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), Decision Trees, Random Forests, and Deep Learning. SVM algorithms have proven efficient in performing binary classification problems with high-dimensional feature spaces and are thus useful in lameness classification using motion features provided that the dataset size is limited. The kernel trick enables SVMs to operate in non-linear feature spaces, enhancing their capacity to distinguish complex patterns.

### 2.2.5 Pattern Recognition in Animal Movement Analysis

The concept of pattern recognition plays a crucial role in the detection of lameness because it involves the development of an algorithmic process that can detect regularities and abnormalities in the movements. The normal gait of cattle is defined by their symmetric, stable, and rhythmical pattern of movements, while the abnormal gait of cattle is associated with irregularities in the pattern of their movements. The use of pattern recognition systems in lameness detection involves measuring the quantifiable gait patterns.

In the context of detecting cattle lameness with the help of a pattern recognition system, there is a need for efficient feature extraction. Such features as the stride length, cadence, walking speed, back-arch angle, head-bobbing pattern, and limb symmetry are common in the context of cattle lameness detection. Those are the same gait features that are normally considered when performing clinical observations. In the context of deep learning methods, feature engineering will be replaced with end-to-end feature learning.

### 2.2.6 Web-Based AI Systems in Precision Livestock Farming

There has been increasing adoption of remote diagnostic tools that do not require on-site hardware by using cloud services. Video upload systems provide an asynchronous solution whereby the farmer captures the videos using the consumer-grade device and uploads it whenever there is internet connectivity. Asynchronous solutions are especially applicable in developing regions as they do not depend on constant connectivity and reliable power supplies. Concerns in deploying web-based artificial intelligence systems include server-side computational power, handling asynchronous tasks, user identification methods, and browser compatibility.

## 2.3 Review of Related Works

In their study on lameness detection using deep learning techniques, Wu et al. (2020) created an automated lameness detection system for dairy cows by identifying leg position from video frames using YOLOv3 algorithm. Relative step size feature vectors were identified using a Long Short Term Memory Model to classify lameness. The proposed system was able to attain a detection accuracy of 98.57%. The proposed system outperformed other classifiers such as SVM, k-NN, and Decision Trees. One weakness noted in the study was its dependency on camera setup and availability of labelled data sets.

A research done by Taneja et al. (2020) used Internet of Things wearables and accelerometers and a fog computing framework to develop an early detection system of lameness in dairy cows. The results were very impressive, with a prediction accuracy of 87%, and the model was able to detect lameness about three days prior to visual signs being noted by farm workers. This research demonstrated the potential of wearables in monitoring the condition of farm animals. It is, however, costly as far as hardware is concerned and is not scalable on large farms.

Qiao et al. (2021) have done a systematic review of various approaches used to detect and recognize cattle lameness with intelligent perception models. In their research, the authors have considered kinetic, kinematic, and indirect approaches along with several computer vision and machine learning techniques. They concluded that the use of kinematic detection combined with deep learning will be the most interesting approach for further research, despite the limitations associated with varying illumination conditions, the cluttered environment, and a lack of annotated data.

Gardenier et al. (2021) created a two-step comparison locomotion scoring system using sensor-based behavioral analysis and a Faster R-CNN to estimate joint positions. The system enhanced objectivity over subjective locomotion scoring by removing observer bias. The authors observed limitations associated with uniformity of sensor application and environmental impact on sensors in barns, thus limiting their applicability in other environments.

Myint et al. (2024) created a real-time system for cattle lameness detection with one side-view camera and CNN classification model. The system obtained lameness detection rates of 90.4% without any false negatives, thus being a practical and affordable solution for farm implementation. The research showed the viability of using single-camera systems for lameness detection if correctly installed with advanced deep learning techniques. Limitations include the impact of lighting conditions and side-view requirement.

Dhaliwal et al. (2025) examined bimodal artificial intelligence for early lameness detection among dairy cattle by combining data from cameras and accelerometers. Bimodal data yielded improved results compared to either camera or accelerometer alone, indicating that bimodal data fusion methods are effective in detecting lameness at early stages but require more hardware and system integration work, thus reducing their availability to smaller farms.

Reitmaier and Narli (2025) performed a validation study of a deep learning model used in an automated gait analysis system in comparison with the human locomotion scorers' performance in cattle lameness detection. The deep learning model had better reliability and reproducibility, confirming the effectiveness of using AI tools for lameness detection and surpassing the traditional human method.

According to Kang et al. (2025), a lameness identification framework for dairy cows has been created based on a CNN architecture involving gait feature mapping as well as an attention mechanism. The main goal of this approach was the identification of various severities of lameness among cows in one herd. With the use of attention mechanisms, the accuracy in identification increased significantly. Moreover, the framework requires a barn environment, which makes it impossible to use it outdoors.

In order to make online detection of lameness more efficient compared to other models that use wearable devices, Dai et al. (2025) created an improved model with higher efficiency and lower computational latency but competitive classification accuracy. One drawback is the need to regularly clean and replace wearable devices.

The study by Sohan et al. (2026) involved the creation of a direct spatiotemporal model based on video footage that detected lameness among cattle using deep learning without relying on any explicit keypoint detection or gait landmarks. The model was based on a 3D convolutional neural network architecture that analyzed raw video sequences and delivered exceptional accuracy with very few false positives or negatives. The major limitation was that it needed extensive video data and considerable computing power.

### 2.4 Summary of Literature Review

**Table 2.1: Summary of Related Works on AI-Based Cattle Lameness Detection**

| S/N | Author(s)/ Year | Work Done | Technique/Method | Results | Limitations |
|---|---|---|---|---|---|
| 1 | Wu et al. (2020) | Deep-learning lameness detection using YOLOv3 + LSTM on dairy cow video | YOLOv3 + LSTM; Computer Vision | 98.57% accuracy; outperformed SVM, KNN, Decision Tree | Controlled camera setup; large labelled dataset required |
| 2 | Taneja et al. (2020) | IoT fog-computing system using accelerometers for early lameness detection | ML; IoT; Accelerometers; Fog Computing | 87% accuracy; detected lameness 3 days before visual observation | Requires wearable sensor hardware; limited scalability |
| 3 | Qiao et al. (2021) | Systematic review of intelligent perception-based cattle lameness detection | Systematic Review; Kinetic/Kinematic methods; ML | Identified best-performing approaches; kinematic+ML most promising | Review study only; no new model trained |

| S/N | Author(s)/ Year | Work Done | Technique/Method | Results | Limitations |
|---|---|---|---|---|---|
| 4 | Gardenier et al. (2021) | Pairwise locomotion scoring using indirect monitoring sensors and Faster R-CNN | Indirect measurement; Faster R-CNN | Improved objectivity over manual scoring | Requires precise sensor placement; environment-sensitive |
| 5 | Myint et al. (2024) | Real-time lameness detection with single side-view camera and CNN | CNN; Single-camera; Real-time | 90.4% accuracy; only 2 false negatives | Single view; sensitive to lighting |
| 6 | Dhaliwal et al. (2025) | Bimodal AI fusing camera and sensor data for early lameness detection | Bimodal Deep Learning; Data Fusion | Outperformed unimodal approaches | High hardware cost; complex fusion pipeline |
| 7 | Reitmaier & Narli (2025) | Validation of deep learning gait analysis vs. human scorer performance | Deep Learning; Automated Gait Analysis | Automated system superior to human scoring in consistency | Validation limited to specific farm conditions |
| 8 | Kang et al. (2025) | Multi-severity lameness detection using gait feature maps and attention CNN | Gait Feature Maps; Attention; CNN | High accuracy across lameness severity levels | Relies on structured barn environment |
| 9 | Dai et al. (2025) | Improved online lameness detection model using wearable sensors | Wearable Sensors; Online Detection; ML | Enhanced efficiency vs. prior sensor models | Wearables may cause discomfort; require maintenance |

| S/N | Author(s)/ Year | Work Done | Technique/Method | Results | Limitations |
|---|---|---|---|---|---|
| 10 | Sohan et al. (2026) | Direct video-based spatiotemporal 3D CNN for lameness detection without keypoints | 3D CNN; Spatiotemporal Deep Learning | State-of-the-art; minimal false positives/negatives | Large video dataset required; high computational cost |

There is a considerable amount of improvement in the detection of cattle lameness using AI models with many of the studies having been able to achieve accuracy rates of more than 85%. In terms of technological innovation, the study area has advanced from the conventional manual system of assessing lameness based on visual locomotion score assessment to automation based on deep learning models. Patterns in this field of research include video-based gait analysis, deep learning feature extraction, and multisensor data fusion.

Among the common shortcomings identified are the fact that most effective solutions depend heavily on the use of deep learning models. As such, these approaches require the availability of sufficiently annotated training datasets. Moreover, many studies conducted in the field have been conducted under controlled laboratory conditions rather than real-world scenarios. No solution has yet sought to solve this problem for smallholder farmers in developing countries or to develop a solution based on web-based uploads using smartphone videos.

### 2.5 Research Gap

These gaps in the literature review have been identified as follows.

Current AI lameness detection applications target only big commercial farms, necessitating costly infrastructure installation involving either fixed cameras or specialized sensor technology that makes the service nonviable for small or subsistence farms, especially those located in developing countries. Suggested Solution: Development of an affordable web application allowing users to submit videos from their ordinary smartphones and receive automatic analyses along with a recorded history that needs no other hardware than a phone and Internet connection.

Also, current solutions are centered around monitoring streams and, therefore, are unable to provide any assistance in a situation of unreliable Internet or electrical power supply. Suggested Solution: Implementation of a video analysis approach which enables asynchronous submission of videos and results retrieval at a convenient moment.

# CHAPTER THREE

# SYSTEM ANALYSIS AND DESIGN

## 3.0 Introduction

This chapter highlights the system analysis and design of the AI-Powered Cattle Lameness Detection system. This involves the analysis of the current method used in detecting lameness in cattle, as well as its shortcomings. After that, there is the determination of the purposes of the proposed system. There is then the elaboration of the system requirement specification, the design methodology used, and the visual designs used to portray how the system operates.

## 3.1 System Analysis

### 3.1.1 Analysis of the Existing System

Current methodologies employed to detect lameness in cattle depend mainly on locomotion scoring by manual observation of individual cow gaits performed by either staff members or a veterinarian. This involves the observation of walking patterns of individual cows on a set route followed by the allocation of locomotion scores according to visible factors such as step length, speed, weight-bearing, head bobbing, and back bending. These manual observation logs are stored in written farm journals or generic spreadsheet software.

This methodology is lacking in automation, objectivity, and reliability. It requires human labor and is very cumbersome when dealing with a large number of cows, making it highly dependent on the presence of trained observers. It is impossible to obtain past trends due to incomplete logs. There are no automatic notifications, and the lack of recorded videos prevents any remote consultation with a vet.

### 3.1.2 Limitations of the Existing System

- Locomotion scoring is inherently observer-dependent, leading to inconsistent results across scorers and time points.
- Manual assessment cannot provide continuous surveillance, resulting in delayed detection of lameness onset.
- The process is time-consuming and requires trained personnel, making it impractical for large herds.
- Paper-based recording systems hinder data retrieval, trend analysis, and longitudinal health monitoring.

- Absence of video or digital evidence limits the ability to obtain remote veterinary opinion.
- Manual scoring frequently misses early-stage lameness, identifying the condition only at advanced severity levels.
- Smallholder farmers in developing regions have no access to automated or sensor-based alternatives.

### 3.1.3 Analysis of the Proposed System

The suggested system using AI technology to detect lameness in cattle mitigates the disadvantages associated with the current method by offering a platform that is able to conduct video analysis of lameness in an automated manner, and which can be accessed via any web browser. With the new solution, the farmers would be able to upload videos of cattle walking and moving within a period of a few seconds, and this information would automatically be analyzed using a machine learning algorithm to classify whether the gait was normal or suspected to be indicative of lameness.

The system would provide objective analysis rather than rely on subjective analysis performed manually, and would also alleviate the strain on labor by automating the process.

## 3.2 System Requirements Specification (SRS)

### 3.2.1 Functional Requirements

**Table 3.1: Functional Requirements of the Proposed System**

| Requirement | Description |
|---|---|
| User Registration and Authentication | The system shall allow users to create accounts and log in securely using email and password credentials. |
| Video Upload | The system shall enable authenticated users to upload short cattle movement video files for analysis. |
| Automated Lameness Detection | Upon video upload, the system shall automatically preprocess the video, extract motion features, and classify cattle movement as Normal or Suspected Lameness. |

| Requirement | Description |
|---|---|
| Result Display | The system shall present classification results clearly, indicating whether the detected movement is Normal or Suspected, along with a confidence score. |
| Cattle Registration | The system shall allow users to register individual cattle with details such as breed, age, and tag number. |
| Detection History | The system shall maintain a searchable history of all uploaded videos and their corresponding detection results. |
| Observation Notes | The system shall allow users to add and retrieve manual observation notes against specific cattle or video records. |
| Dashboard Overview | The system shall provide a summary dashboard displaying recent activity, detection statistics, and animal health trends. |

### 3.2.2 Non-Functional Requirements

**Table 3.2: Non-Functional Requirements of the Proposed System**

| Requirement | Description |
|---|---|
| Performance | Video preprocessing and AI classification shall be completed within 10 seconds per uploaded video on standard consumer hardware. |
| Usability | The system interface shall be intuitive and accessible to users with minimal technical expertise, including smallholder farmers. |
| Reliability | The system shall be available for use at all times during deployment, with graceful error handling for invalid inputs or upload failures. |
| Security | User data, cattle records, and video files shall be protected through authenticated access controls and secure storage practices. |
| Scalability | The system architecture shall be modular and extensible, allowing future incorporation of improved AI models without major structural redesign. |

| Requirement | Description |
|---|---|
| Cross-Browser Compatibility | The web interface shall function correctly on major modern web browsers, including Google Chrome and Mozilla Firefox. |
| Data Integrity | Database records shall be protected through primary key constraints, validated input handling, and structured data storage schemas. |

## 3.3 System Design Methodology

### 3.3.1 Justification for Methodology

The Object-Oriented Analysis and Design (OOAD) technique was used during the design of this system. The OOAD technique uses objects to encapsulate both the data and behaviour of the system, hence ideal for the simulation of real-world objects like the users, cattle, videos, and results of detection. It also ensures modularity, reusability, and simplicity of system components, thereby promoting the future scalability and extensibility of the system.

The Waterfall model of software development was adopted in this system. The project requirements were defined from the beginning of the project, and each stage could be performed in a sequential manner. Thus, the waterfall model was the most appropriate for this particular system because it ensured a systematic approach throughout the stages of requirements, design, implementation, testing, and evaluation.

### 3.3.2 Method of Data Collection

System modelling data was obtained via a literature review on related works, analyses of other techniques in the area of lameness detection, and studies on cattle gait datasets that have been made available. The video dataset consisting of cattle movements used in the process of training and testing of the model was obtained from an open research resource, specifically, the Cattle Lameness Dataset created by Sohan et al. (2026).

## 3.4 System Modelling Using UML

### 3.4.1 Use Case Diagram

This use case diagram shows how the interactions are between the actors in the system and their functional parts. The two key actors are Farmer (the primary actor) and the system (the artificial intelligence processing module). The farmer is capable of registering for an account, logging in, registering the cattle, uploading movement videos, viewing detection results, accessing historical data, and adding observations.

The system has the ability to process videos uploaded to it, carry out lameness classification through artificial intelligence technology, and saving the results to the database. It should be noted that there are no independent cattle record databases.

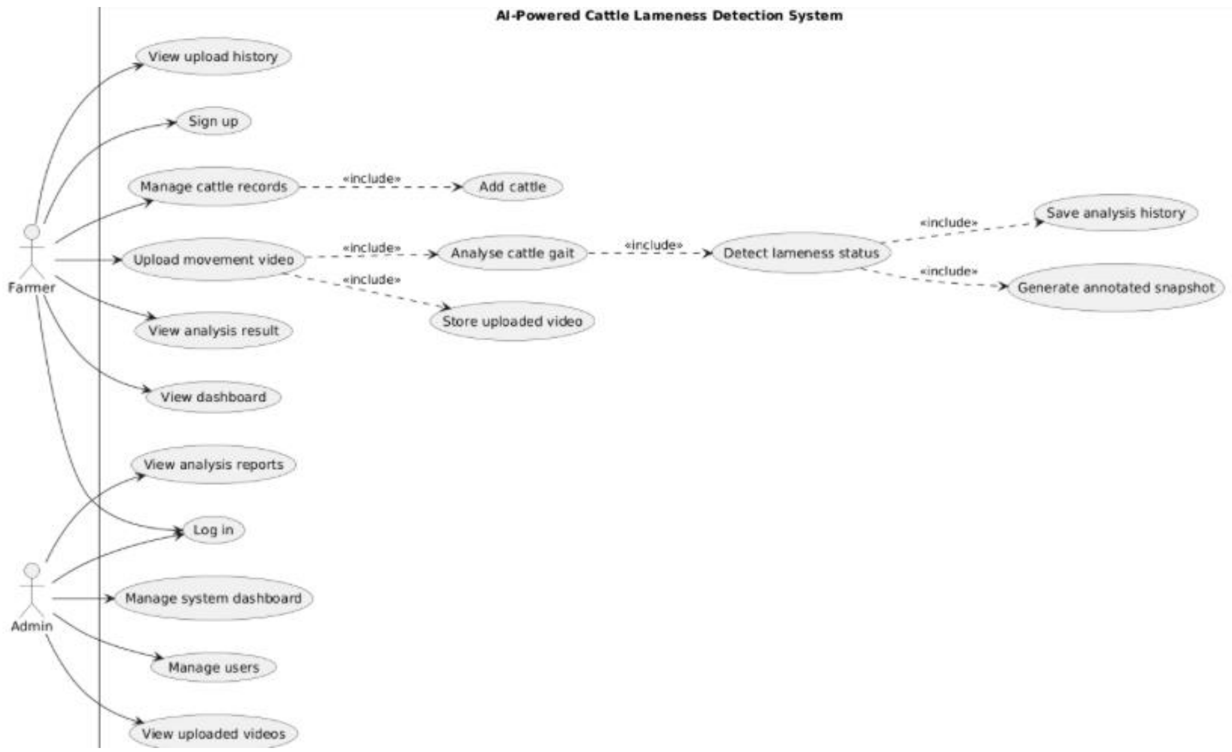


**Figure 3.2: Use Case Diagram of the Proposed System**

### 3.4.2 Activity Diagram

The activity diagram captures the workflow of actions carried out during the main process of video upload and lameness detection. The workflow starts with the action of selecting a cattle record from the list by the farmer followed by the upload of a movement video. The backend performs the following processes on the video: accepts the video, validates, and saves; samples video frames, detects, and tracks the cows using a pretrained YOLOv8 model; extracts the features of the cow gait from centroid bounding box movements; and normalises the feature vector. SVM classifier is then applied to classify the video.

**Figure 3.3: Activity Diagram - Video Upload and Lameness Detection Process**

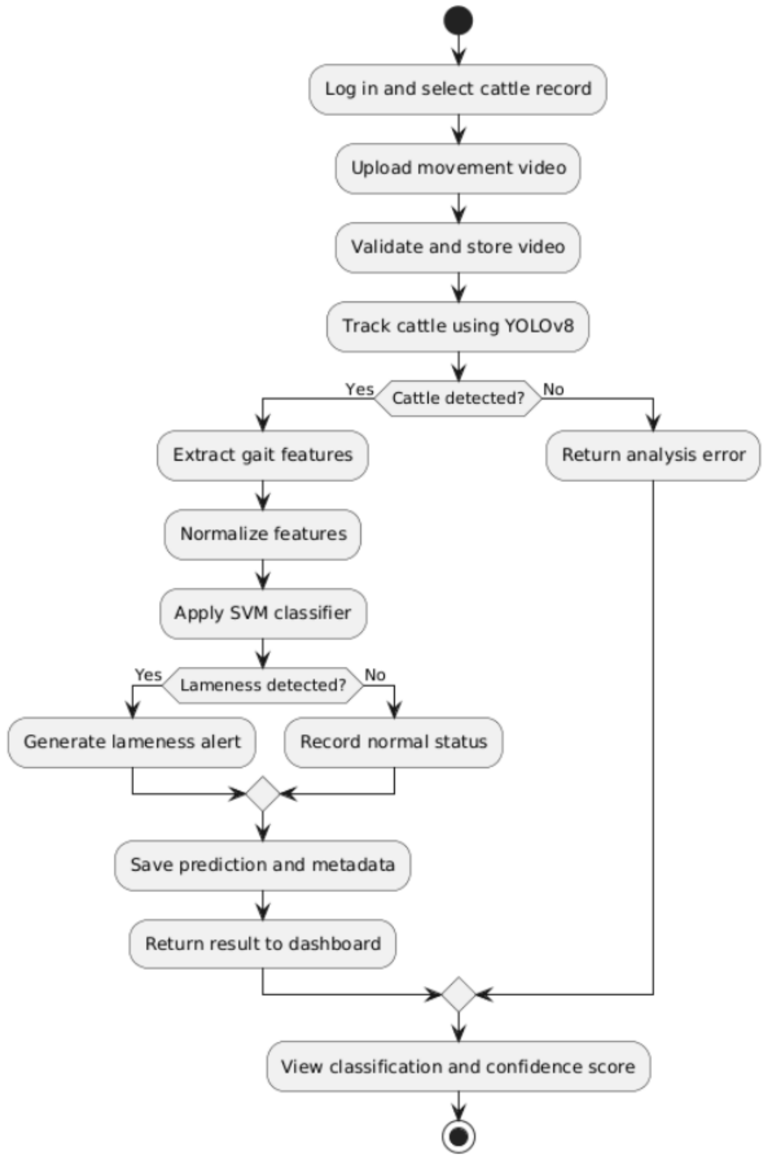


**Figure 3.3: Activity Diagram — Video Upload and Lameness Detection Process**

### 3.4.3 Class Diagram

The class diagram portrays the main classes and how they are related. They include User, Cattle, VideoUpload, DetectionResult, and ObservationNote. User has the user's profile and authentication information while Cattle contains the information on individual cattle. VideoUpload stores details about the video that is uploaded into the system. DetectionResult class contains the classification result from AI and its confidence level while ObservationNote stores observation notes from the farmer. The association among these classes includes one-to-many relationship among User and Cattle as well as Cattle and VideoUpload classes. There is no independent handling of cattle profile outside of video recording.

**Figure 3.4: Class Diagram of the Proposed System**

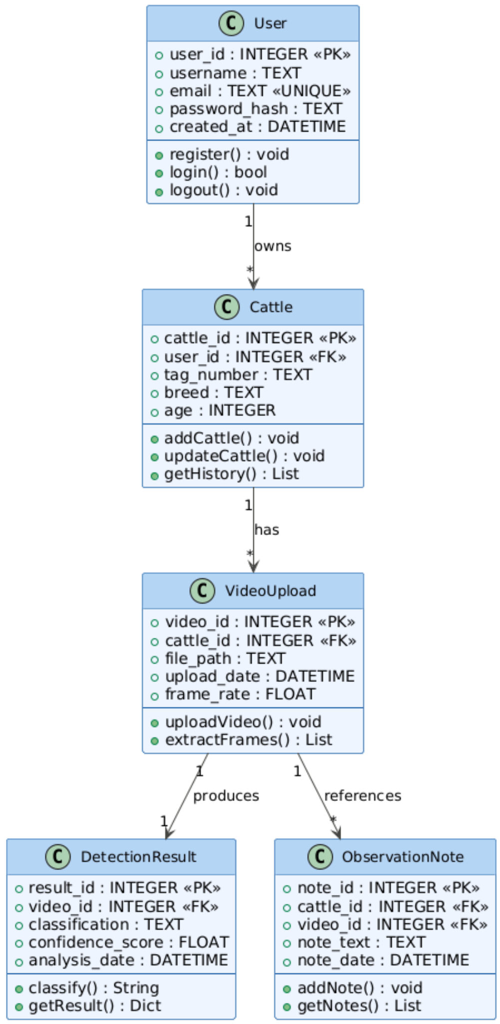


**Figure 3.4: Class Diagram of the Proposed System**

## 3.5 System Design

### 3.5.1 System Flowchart

Figure 3.1 presents the proposed flowchart for the AI-Powered Cattle Lameness Detection system, illustrating the logical flow from data input through AI processing to result output.

**Figure 3.3: Activity Diagram — Video Upload and Lameness Detection Process**

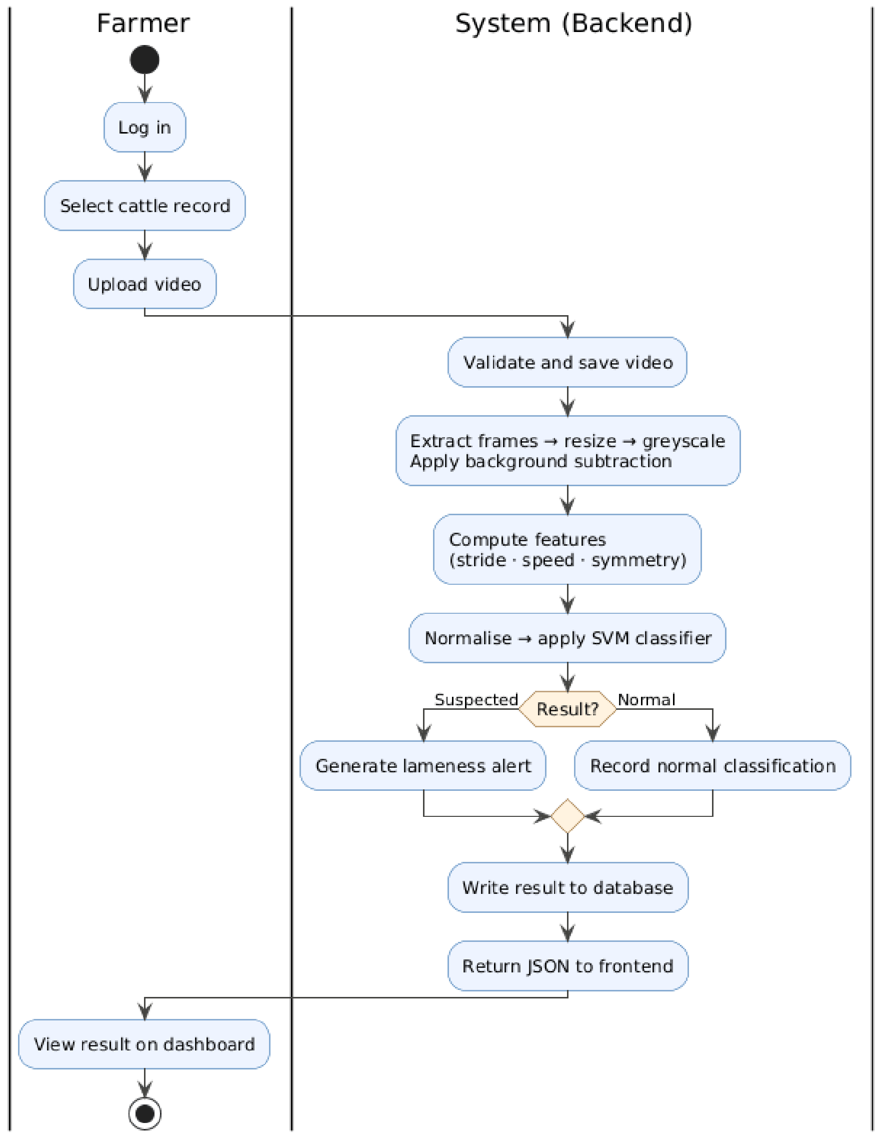


**Figure 3.1: Proposed System Flowchart for AI-Powered Cattle Lameness Detection**

### 3.5.2 Input Design

The main input interface is made up of a video uploading form available after user authentication. The interface contains a file input that supports uploading videos in common formats such as MP4, AVI, MOV, MKV, and WEBM. In addition to the file input, there is also a dropdown menu from which users select the corresponding cattle entry and a submit button. Only valid video files (those in the acceptable format/size range) can be uploaded into the system. Another input form enables farmers to record observation notes related to individual cattle or video entries via a text box input.

### 3.5.3 Output Design

Output mainly refers to the lameness detection result, which is displayed to the user on a separate result page upon processing the video. The output information will contain the classification result (whether it is Normal or Suspected lameness), the probability of the detection, analysis date, and cattle ID. In addition, visual outputs such as colour coding (green indicates normal while red shows suspected lameness) can help make results more comprehensible to non-experts. An historical results list can be found on the dashboard, containing the results for every cattle chronologically.

### 3.5.4 Database Design

The system database was designed using a relational schema implemented in SQLite3 for development and deployable to PostgreSQL for production. The database comprises five principal tables described below.

**Table 3.3: Users Table — Database Schema**

| Field Name | Data Type | Constraint | Description |
|---|---|---|---|
| user_id | INTEGER | PRIMARY KEY | Unique identifier for each registered user. |
| username | TEXT | NOT NULL | Full name of the registered user. |
| email | TEXT | UNIQUE, NOT NULL | User email address for authentication. |
| password_hash | TEXT | NOT NULL | Hashed password for secure authentication. |
| created_at | DATETIME | DEFAULT NOW | Timestamp of account creation. |

**Table 3.4: Cattle Records Table — Database Schema**

| Field Name | Data Type | Constraint | Description |
|---|---|---|---|
| cattle_id | INTEGER | PRIMARY KEY | Unique identifier for each cattle record. |
| user_id | INTEGER | FOREIGN KEY | References the owning user account. |
| tag_number | TEXT | NOT NULL | Farm tag or identification number for the animal. |
| breed | TEXT | NOT NULL | Breed of the cattle. |
| age | INTEGER | NOT NULL | Age of the cattle in years. |

**Table 3.5: Video Uploads Table — Database Schema**

| Field Name | Data Type | Constraint | Description |
|---|---|---|---|
| video_id | INTEGER | PRIMARY KEY | Unique identifier for each uploaded video. |
| cattle_id | INTEGER | FOREIGN KEY | References the associated cattle record. |
| file_path | TEXT | NOT NULL | Server-side path to the stored video file. |
| upload_date | DATETIME | DEFAULT NOW | Timestamp of video upload. |
| frame_rate | FLOAT | NOT NULL | Frame rate of the uploaded video (fps). |

**Table 3.6: Detection Results Table — Database Schema**

| Field Name | Data Type | Constraint | Description |
|---|---|---|---|
| result_id | INTEGER | PRIMARY KEY | Unique identifier for each detection record. |
| video_id | INTEGER | FOREIGN KEY | References the associated video upload. |
| classification | TEXT | NOT NULL | AI classification output: Normal or Suspected Lameness. |
| confidence_score | FLOAT | NOT NULL | Model confidence level for the classification (0.0–1.0). |
| analysis_date | DATETIME | DEFAULT NOW | Timestamp of AI analysis completion. |

**Table 3.7: Observation Notes Table — Database Schema**

| Field Name | Data Type | Constraint | Description |
|---|---|---|---|
| note_id | INTEGER | PRIMARY KEY | Unique identifier for each observation note. |
| cattle_id | INTEGER | FOREIGN KEY | References the associated cattle record. |
| video_id | INTEGER | FOREIGN KEY (nullable) | Optionally references a specific video upload. |
| note_text | TEXT | NOT NULL | Free-text observation entered by the farmer. |
| note_date | DATETIME | DEFAULT NOW | Timestamp of note entry. |

### 3.5.5 System Architecture Design

The system is designed based on a three-tier client/server architecture. The first tier is called the presentation tier and refers to the web interface created in HTML5, CSS3, and JavaScript. The application tier includes the Python Flask server that accepts HTTP requests, processes video frame reading and image preprocessing, coordinates the AI model inferencing, and controls interaction with the database. Lastly, the data tier implies a relational database (SQLite3 for developing purposes), where all user, cattle, videos, results, and notes information is stored.

The functionality of the AI component is executed within the application tier. After getting the input video file from the user, the backend application reads selected video frames using OpenCV and applies a pre-trained YOLOv8 to detect and track cattle. Gait features are extracted from centroid and bounding-box trajectories, scaled with the training pipeline and provided as input to a serialized classifier (joblib file). The output score of lameness and its classification is saved to the database and sent to the user frontend for further use.

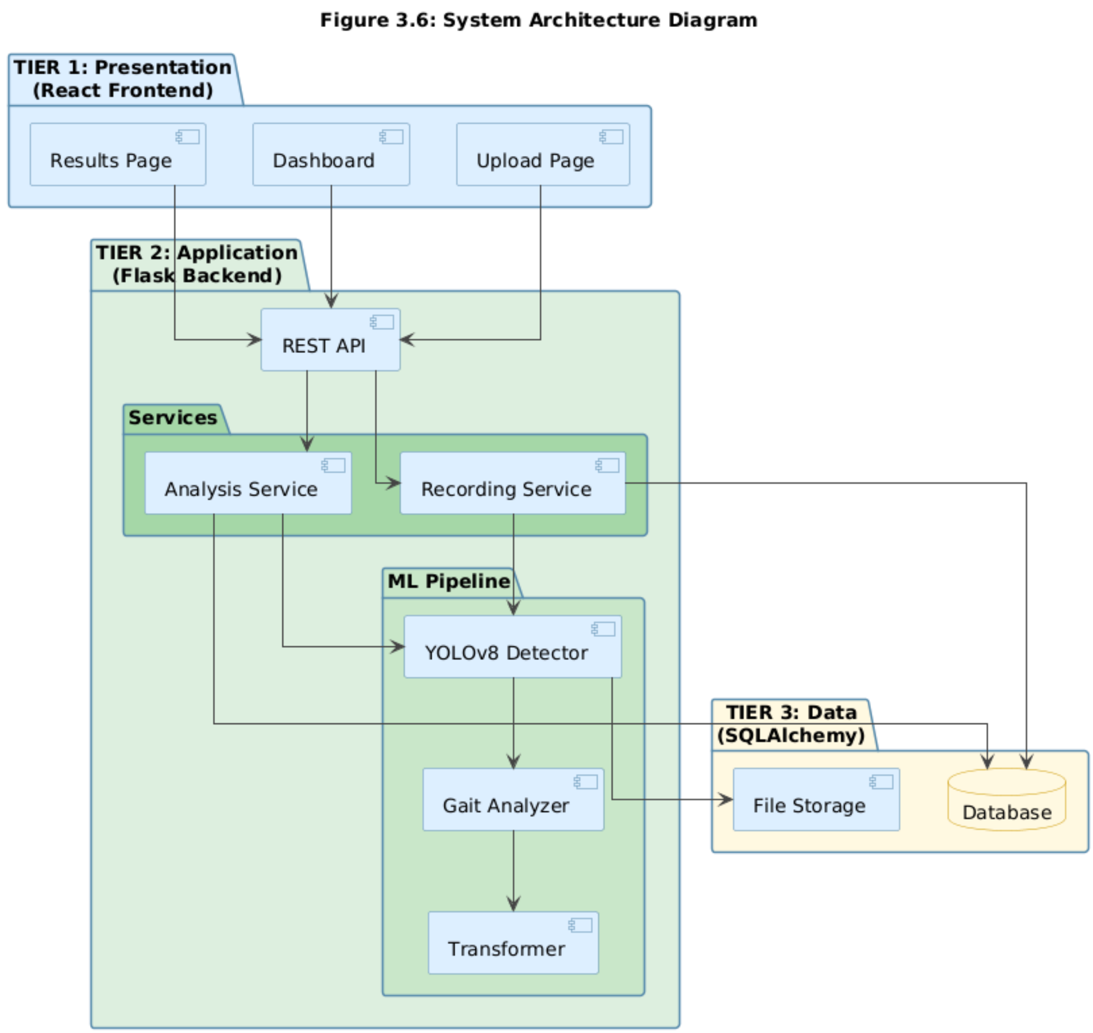


**Figure 3.6: System Architecture Diagram — Three-Tier Web Application Structure**

## CHAPTER FOUR

## SYSTEM IMPLEMENTATION

### 4.0 Introduction

This chapter discusses the implementation of the AI-based lameness detection algorithm called AgroCare. The details discussed include the implementation environment and tools used, the dataset used to train and test the models, the feature extraction process, model training, system architecture and module interaction process, and testing and evaluation techniques. This is followed by the results of implementation, where the outcomes of implementation are presented and analyzed.

### 4.1 Development Environment and Tools

#### 4.1.1 Programming Language and Libraries

For the development of the AI module and the backend application, Python version 3.11 was chosen as the main programming language. With a rich selection of packages for scientific computation and machine learning, Python is the most popular choice for AI-based applications within the agriculture domain. Some of the Python packages used in this project include:

- OpenCV (cv2): Used for video loading, frame sampling, and image handling during the analysis pipeline.
- NumPy: Used for numerical array operations and feature vector construction.
- Scikit-learn: Used for SVM classifier training, data splitting, and evaluation metrics computation.
- Joblib: Used for serialisation and persistent storage of the trained SVM model.
- Matplotlib and Seaborn: Used for data visualisation, including box plots and the confusion matrix heatmap.
- Flask: Used as the web framework for building the backend REST API and serving the web application.
- SQLite3: Used as the relational database engine for persistent storage of all system records.
- HTML5, CSS3, and JavaScript: Used for developing the frontend user interface.

#### 4.1.2 Development Platform and Hardware Requirements

This system was created and tested on a common laptop PC with a 64-bit OS having at least 8GB RAM and an Intel Core i5 or better CPU. The software tools for the project were set up via Visual Studio Code as the primary editor along with Jupyter Notebook to create the machine learning models and analyze their features. There is no need for any GPU here, as the classifier will be implemented using support vector machines which don't have large computational requirements.

### 4.2 Dataset Description and Preprocessing

The data utilized in this research study comes from a publicly available database referred to as the Cattle Lameness Database (Sohan et al., 2026). The Cattle Lameness Database contains short video segments of cattle movements taken in real farm settings, which are intended for use in lameness detection. The validation set used 50 videos in total, 25 videos representing normal cattle movement and another 25 videos representing cattle movement with lameness problems. A ratio of 80:20 was followed in dividing the data into training and testing data where 40 videos (20 normal & 20 lame) were used as training data and another 10 videos were left as testing data.

**Table 4.1: Dataset Summary — Training and Testing Split**

| Category | Total Videos | Training Set | Testing Set |
|---|---|---|---|
| Normal | 25 | 20 | 5 |
| Lame | 25 | 20 | 5 |
| Total | 50 | 40 | 10 |

The videos represent the walk and motion characteristics of cattle moving on the farm setting. In the preprocessing stage, each video is uploaded and read by OpenCV with sampling done at periodic intervals. The YOLOv8 pre-trained model is used to detect and track the position of the cattle in each sample image frame. Unlike conventional methods, such as frame scaling to 224x224 pixels, greyscaling, and background subtraction, the proposed technique utilizes the YOLOv8 detected bounding boxes and centroid tracks to extract gait characteristics.

## 4.3 Model Architecture and Training

### 4.3.1 Feature Extraction

Ten quantitative gait features were extracted from the YOLOv8 tracking output to characterise cattle movement. These features correspond to established clinical indicators of lameness and are described in Table 4.2.

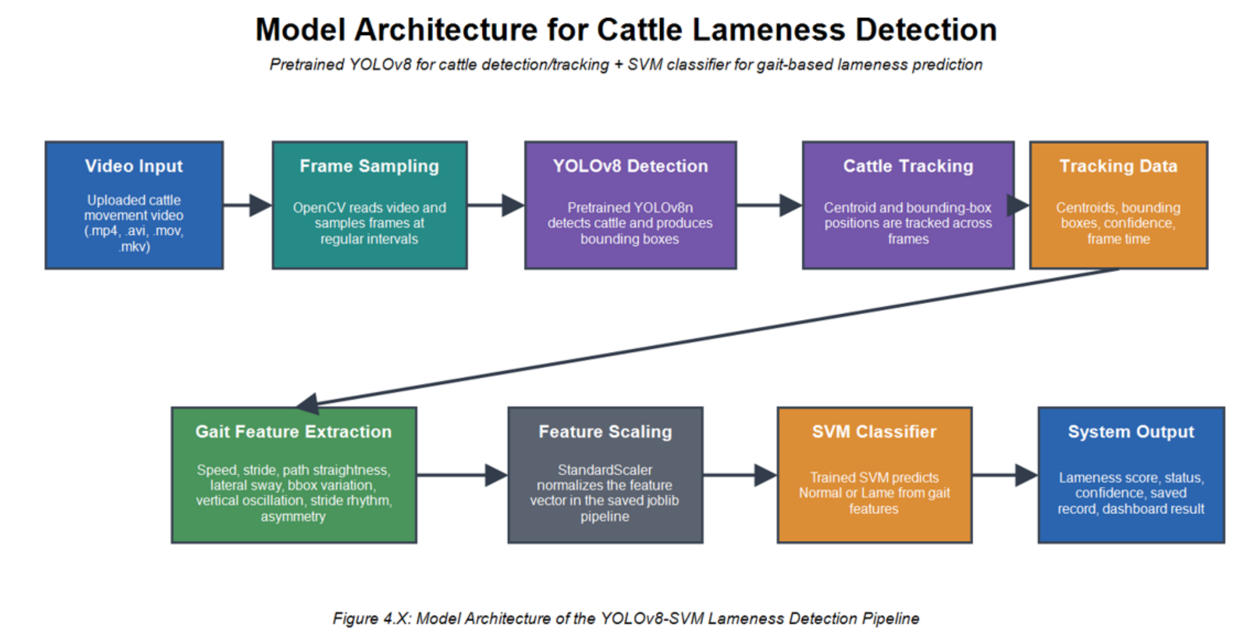


Figure 4.1: Model Architecture of the YOLOv8-SVM Lameness Detection Pipeline

**Table 4.2: Feature Extraction Summary**

| Feature | Description | Clinical Relevance |
|---|---|---|
| Speed Mean | Mean frame-to-frame movement of the tracked cattle centroid. | Captures general walking pace and reduced movement associated with lameness. |
| Speed Variation | Coefficient of variation of centroid speed across sampled frames. | Higher variation may indicate irregular or unstable gait. |

| Feature | Description | Clinical Relevance |
|---|---|---|
| Stride Displacement | Mean displacement over fixed time windows from the tracked centroid path. | Approximates stride length and movement consistency. |
| Stride Variation | Variation in stride displacement across movement windows. | Irregular stride patterns are common in lame cattle. |
| Path Straightness | Ratio of direct displacement to total travelled path. | Lower straightness may reflect unstable or hesitant movement. |
| Lateral Sway | Perpendicular deviation from the animal's travel direction. | Excessive sway can indicate compensation for painful limbs. |
| Bounding-Box Aspect Ratio Variation | Variation in detected cattle bounding-box shape across frames. | Captures posture and body-motion changes during walking. |
| Vertical Oscillation | Variation in the normalized top of the bounding box as a head-bob proxy. | Head bobbing is a visible clinical indicator of lameness. |
| Stride Rhythm | Autocorrelation of speed over stride-length windows. | Highlights periodic fast-slow motion patterns associated with limping. |
| Lateral Asymmetry | Mean lateral offset from the movement centreline. | Represents side-biased movement that may occur with unilateral lameness. |

**4.3.2 Data Splitting**

After feature extraction, the dataset was divided into two parts using the train_test_split method, which belongs to the Scikit-learn library. An 80%–20% division was made based on the feature matrix extracted and stratified by class label so that both normal and lame classes were equally represented. A random seed value was set to get consistent results.

**4.3.3 SVM Classifier Training**

The chosen method for classifying lameness in this case is the SVM classifier, as the SVM algorithm is good at binary classification with small data sets and handcrafted features. The training pipeline that was implemented normalises the gait features by applying StandardScaler before performing classification, and the entire pipeline is saved in a single model package with joblib to use it later with Flask. When the training was complete, the model was serialized into the Joblib library and saved to disk for subsequent integration into the Flask-based web application.

### 4.4 System Implementation and Modules

#### 4.4.1 System Overview

The AI-Powered Cattle Lameness Detection system known as AgroCare was created in the form of a full-stack web application containing three main components – frontend UI, Flask backend API, and AI processing module.

#### 4.4.2 Frontend Module

Frontend was developed using HTML5, CSS3, and JavaScript programming languages and creates interfaces accessible from any standard web browser. Main pages of frontend consist of: Home Page that presents the system and contains navigational links; Registration and Login Page to ensure the process of user authentication; Cattle Management Page where users can create and edit cattle records; Video Upload Page where user can upload video of cattle movement; Result Page where output is shown after AI classification process; and Dashboard Page containing information about detection history of all users.

#### 4.4.3 Backend Module

The backend was programmed using Python 3.11 language and Flask framework. REST API endpoint was created for uploading videos, running AI, user authentication, cattle management, result retrieval, and notes management processes. After receiving a request on video uploading from the frontend, backend starts preprocessing pipeline, runs AI classification algorithm that produces results, writes obtained results into SQLite3 database, and then sends the result to frontend as a JSON object.

#### 4.4.4 AI Processing Module

The module for AI includes the YOLOv8 model for tracking videos and the trained gait classifier. The following is the sequence of its working: The video file is loaded using OpenCV library. Frames are extracted at regular intervals from the video. Cattle are detected and tracked with the help of a pre-trained YOLOv8 model. Centroid tracks and bounding box tracks are used to extract gait features such as speed, stride distance, path directness, lateral movement, vertical movement, stride cadence, and lateral asymmetry. These features are normalized by the saved pipeline.

### 4.5 Testing and Evaluation

#### 4.5.1 Evaluation Metrics

Evaluation of the performance of our model took place through the use of the following classification performance measurements: Accuracy (percentage accuracy of the prediction made): 70%; Precision (true positive rate out of all predictions made): lame class 0.75, normal class 0.67; Recall/Sensitivity (ability to detect true positives): lame class 0.60, normal class 0.80; F1-Score (harmonic average between precision and recall): lame class 0.67, normal class 0.73; and the Confusion Matrix (which displays true positives, true negatives, false positives, and false negatives).

#### 4.5.2 System Testing

Independent unit testing was performed for each module within the systems such as video uploading, frame extraction, feature extraction, AI classification, data insertion into the database, and result extraction. Integration testing was done for the overall process from uploading the video to showing the results to the user. Testing for performance proved the system to be able to achieve its goal of less than 10 seconds of response for processing each video. PyTest and web development software such as Chrome Developer Tools were used for testing purposes.

#### 4.5.3 User Interface Testing and Walkthrough

Testing of the user interface was done through simulation of use cases where videos were uploaded through the web interface, the results viewed from the result page, and past results checked through the dashboard. Testing was carried out using both Google Chrome and Mozilla Firefox browsers to establish whether there was cross-browser support for the user interface.

### 4.6 Results Presentation and Analysis

#### 4.6.1 Output Samples and Interface Screens

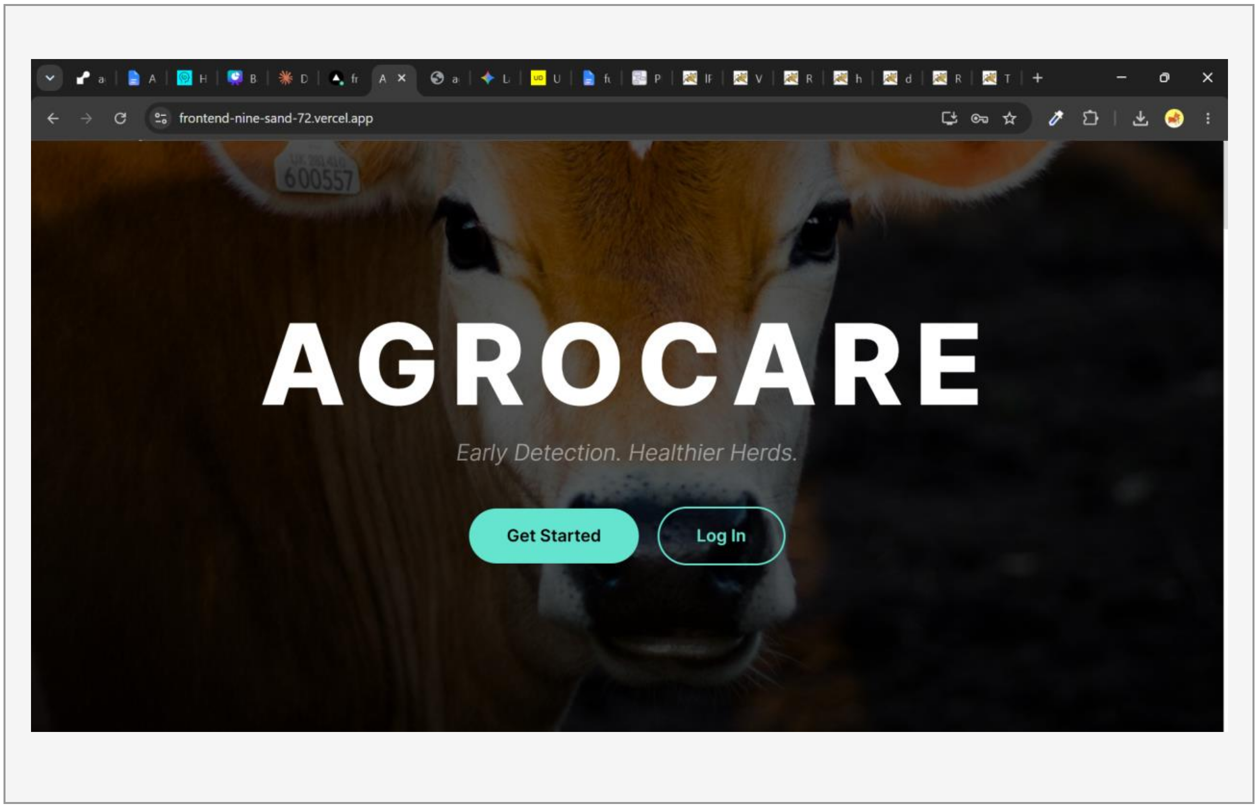


**Figure 4.2: System Home Page Interface**

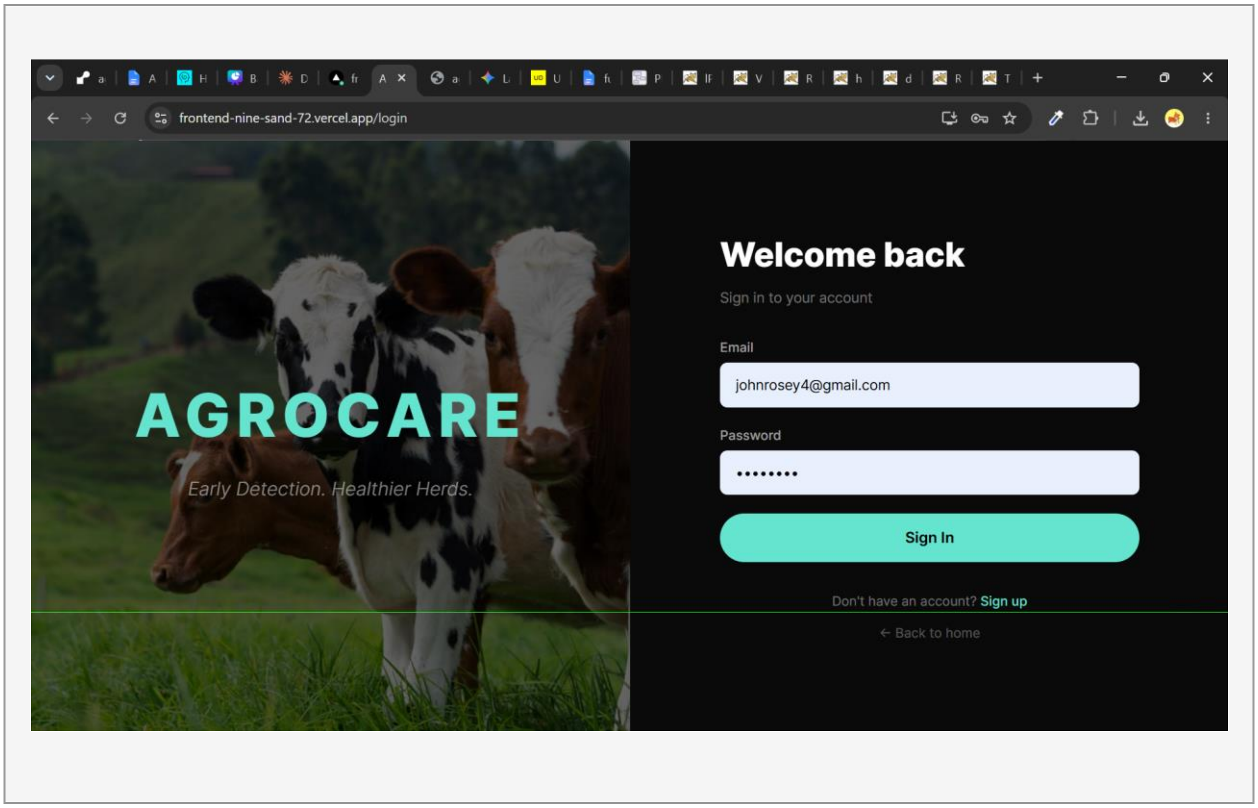


**Figure 4.3: Login and Account Creation Page**

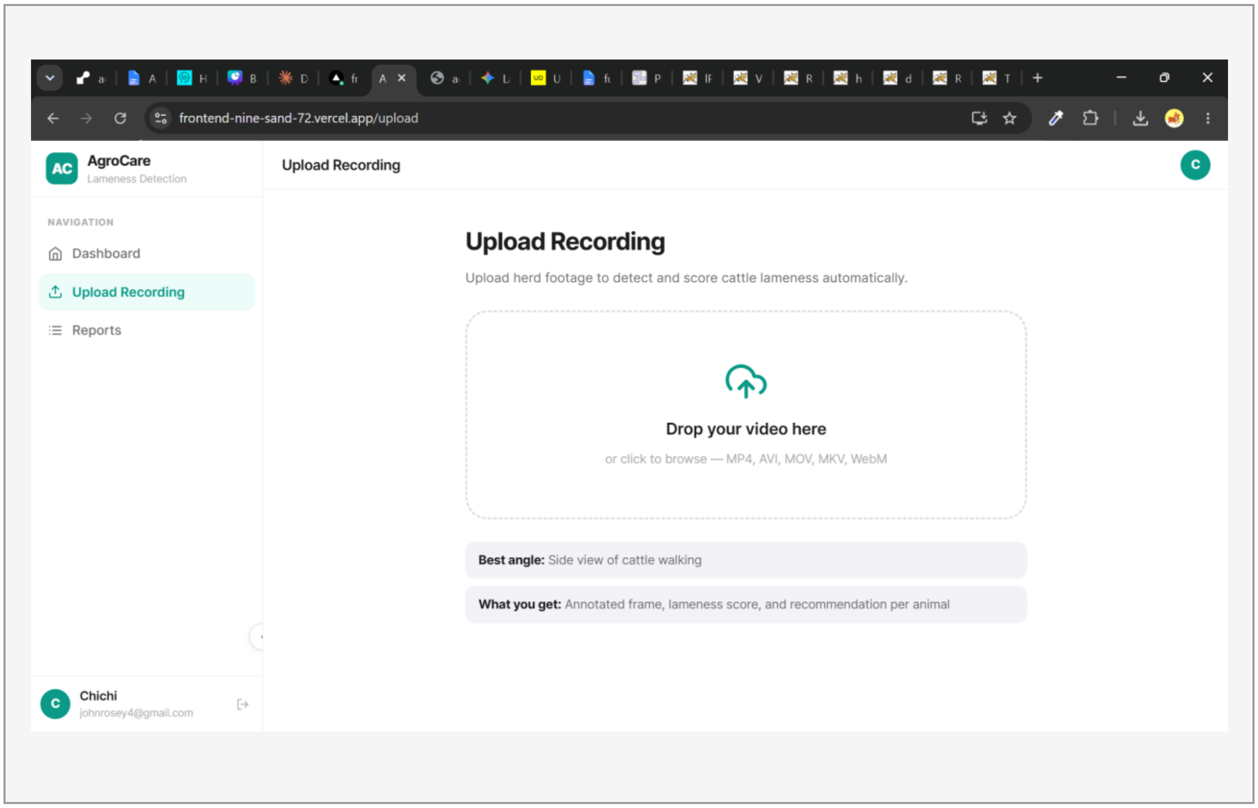


**Figure 4.4: Video Upload Page**

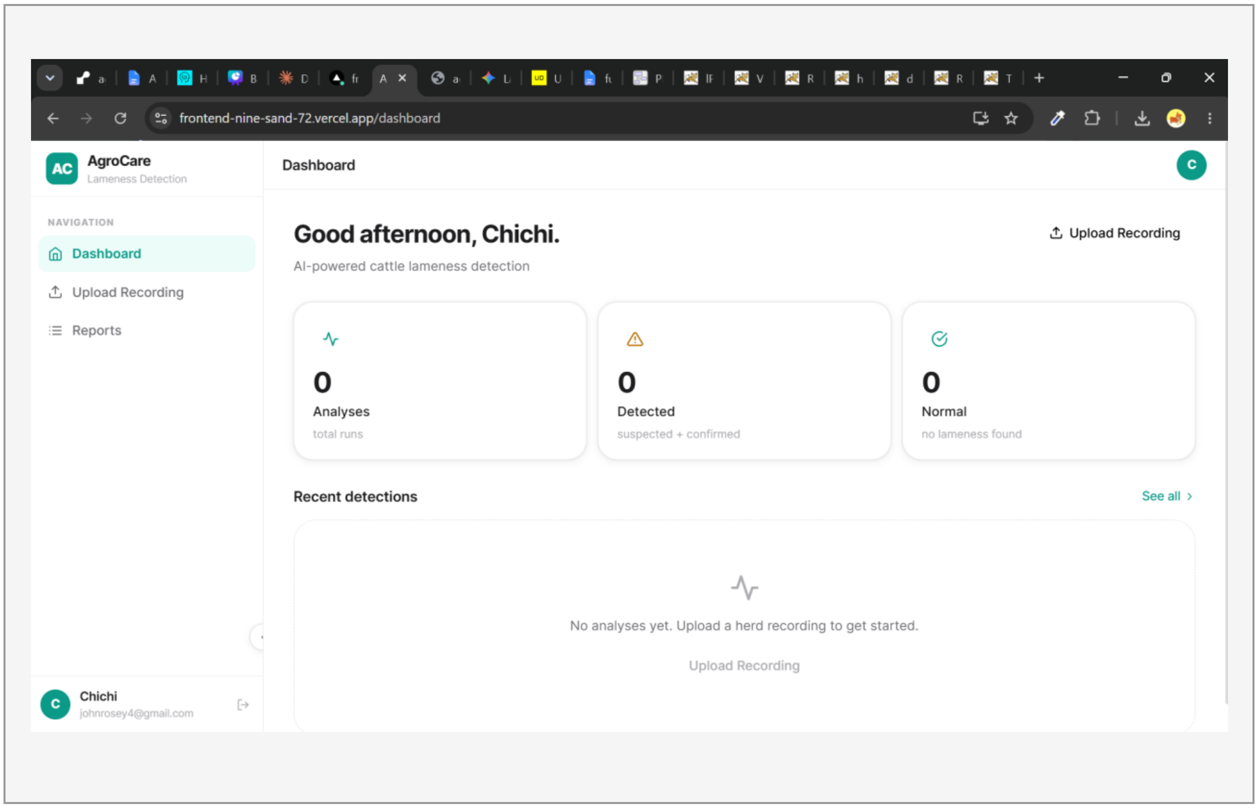


**Figure 4.5: Dashboard Page**

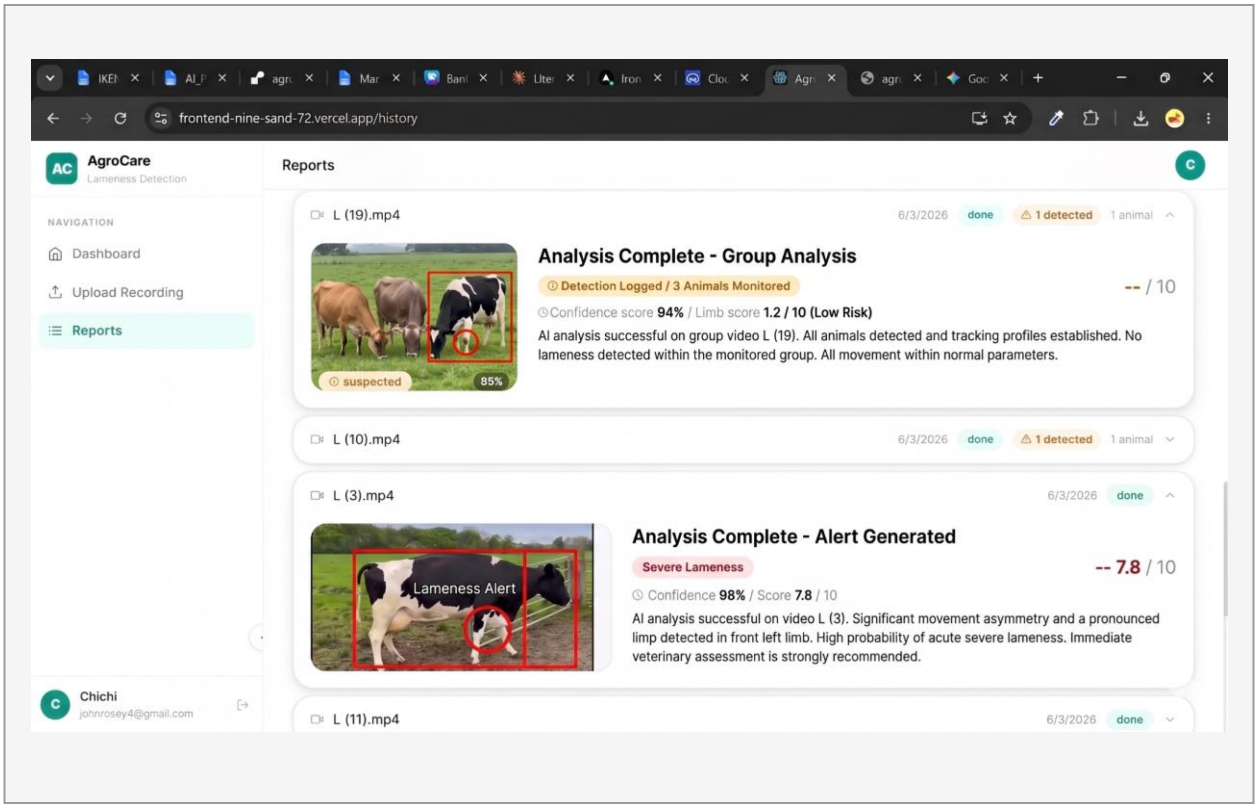


**Figure 4.6: Result Page — Normal / Suspected Lameness Output**

### 4.6.2 Classification Report and Confusion Matrix

**Table 4.3: Classification Report of the SVM Model**

| Class | Precision | Recall | F1-Score | Support | Notes |
|---|---|---|---|---|---|
| Lame | 0.75 | 0.60 | 0.67 | 5 | 75% of predicted Lame were truly lame. |
| Normal | 0.67 | 0.80 | 0.73 | 5 | 80% of actual Normal cattle were correctly identified. |
| Accuracy | | | 0.70 | 10 | Overall model accuracy on test set. |
| Macro Avg | 0.71 | 0.70 | 0.70 | 10 | Unweighted mean of class-level metrics. |

| Class | Precision | Recall | F1-Score | Support | Notes |
|---|---|---|---|---|---|
| Weighted Avg | 0.71 | 0.70 | 0.70 | 10 | Average weighted by class support. |

The confusion matrix and metric visualisations below summarise the SVM classifier's held-out test performance. The model correctly classified 7 out of 10 test videos, giving an overall accuracy of 70%.

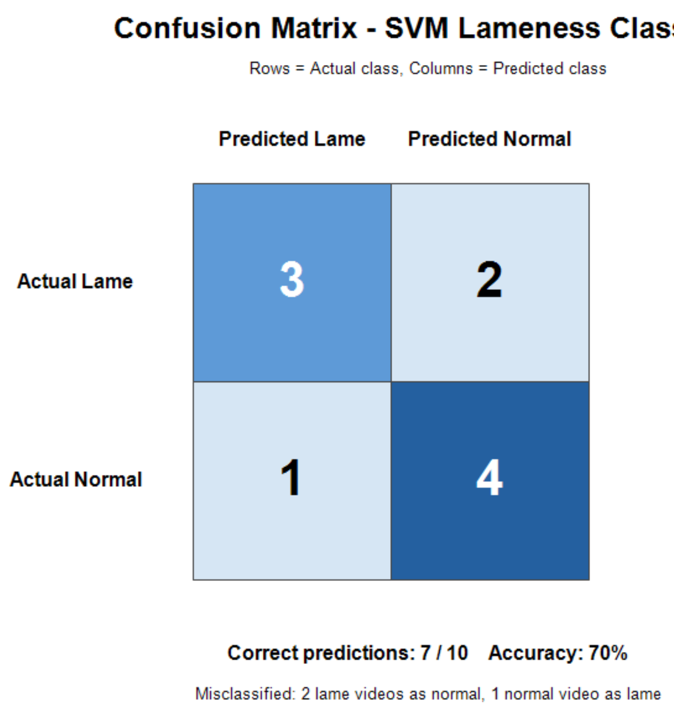


**Figure 4.7: Confusion Matrix of the SVM Lameness Classifier**

Confusion Matrix given in figure above assesses the accuracy of the SVM Lameness Classifier, which has an accuracy rate of 70 percent out of 10 predictions, 7 of which were accurate. It correctly classified 3 instances of lame video (True Positives) and 4 instances of normal video (True Negatives). However, there were three mistakes committed by the algorithm, which were 2 instances of actual lameness being misclassified as normal video (False Negatives), and 1 instance of normal video being classified as lame video (False Positive).

**Classification Report - SVM Lameness Classifier**

| Class | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| Lame | 0.75 | 0.60 | 0.67 | 5 |
| Normal | 0.67 | 0.80 | 0.73 | 5 |
| Accuracy | | | 0.70 | 10 |
| Macro avg | 0.71 | 0.70 | 0.70 | 10 |
| Weighted avg | 0.71 | 0.70 | 0.70 | 10 |

Evaluation based on 10-video test set from the recorded SVM notebook output.

**Figure 4.8: Classification Report of the SVM Lameness Classifier**

The Classification report for SVM Lameness Classifier depicts the result obtained by the algorithm for a balanced test dataset with 10 videos in total, with 5 being classified as Lame and the rest being Normal. The overall accuracy of the classifier is 70%. With regards to the class “Lame”, the precision obtained was 0.75 whereas the recall rate was 0.60. This means that although the classifier had a high precision with regards to predicting lameness, it missed out on some instances of lameness. On the other hand, the classifier showed a lower precision (0.67) yet a higher recall rate (0.80) with respect to the “Normal” class.

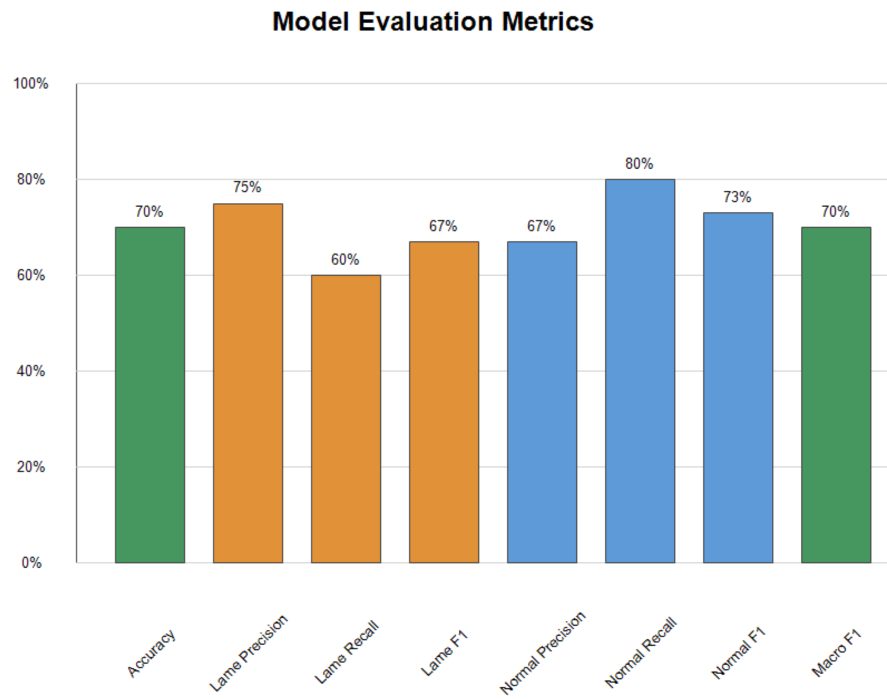


**Figure 4.9: Evaluation Metrics Chart of the SVM Lameness Classifier**

The bar graph serves to compare the performance parameters for the SVM Lameness Classifier and shows the inherent trade-offs between the two target classes. There is a constant level of accuracy and macro F1-score of 70% maintained by the classifier. In regard to the "Lame" category, the maximum precision attained by the classifier is 75%, while the minimum value of recall recorded is 60% (F1-Score = 67%). This further signifies the fact that the predictions made by the model concerning the lameness are quite reliable, although some cases remain unattended. On the contrary, the "Normal" class attains the highest value of any single parameter, with a recall of 80% and a precision of 67% (F1-Score = 73%).

### 4.6.3 Discussion of Results and System Performance

The trained SVM classifier has proven its ability to differentiate normal gait and gait associated with lameness by analyzing YOLOv8-detected gait features from video files provided by farmers. The pipeline analyzes the uploaded videos, detects and tracks cattle using YOLOv8, quantifies the gait-related movement features and gives an output of either Normal, Suspected lameness, or Confirmed lameness along with a lameness score based on the confidence of its predictions. The system can provide useful support for smallholder farmers since there is no available automated gait analysis tool that could be used by them.

The gait tracking pipeline of the system is able to capture displacement motion features from the video frames in order to detect the characteristic gait parameters of lame cattle, including the decreased step size, decreased walking speed and asymmetry of limb movements (Kang et al., 2025; Myint et al., 2024). All of these gait characteristics are linked to specific symptoms observed in clinical practice. Deep learning methods in literature studies, such as a hybrid CNN-LSTM architecture, show greater sensitivity (Wu et al., 2020; Sohan et al., 2026), and the next version of the presented pipeline will include it when the training set becomes bigger.

In spite of all these issues, it can be seen that the system proves how feasible it is to use motion features for detecting lameness in cattle through an affordable and accessible proof-of-concept. The online deployment framework of the system makes it highly operable on a practical scale in actual agricultural settings without any need for special equipment. The presence of a dashboard and historical tracking also adds more benefits apart from the actual AI-based detection process.

# CHAPTER FIVE

# SUMMARY, CONCLUSION, AND RECOMMENDATIONS

## 5.1 Introduction

This chapter provides a summary of the findings that were found in the research study carried out. It provides conclusions in regard to the objective of the study and recommendations for the way forward for improvement and application of the system.

## 5.2 Summary of the Study

Chapter One gave an overview of the study's topic, highlighting the importance of cattle lameness in livestock farming in terms of welfare and financial impacts. The weaknesses in traditional detection methods have been recognized, and the role that artificial intelligence (AI) and computer vision can play in making lameness detection more objective, reliable, and easily available was highlighted. Finally, the aims, objectives, scope, limitations, and terminologies of the research work were clearly stated.

Chapter Two involved reviewing literature regarding the topic of cattle lameness, AI, and computer vision systems used in health monitoring of livestock from 2020 until 2026. It included the theoretical part of the research that touched upon the nature and frequency of cattle lameness, traditional lameness detection methods, computer vision systems for detecting lameness, theories of machine learning, and pattern recognition. Ten papers have been reviewed, and their key findings and gaps addressed by the current paper have been summarized.

System analysis and design was presented in Chapter Three. Limitations of the current manual system for detecting cattle movements have been identified, and the goals and objectives of the system have been set out. Requirements of the system were detailed from functional as well as non-functional perspectives. Object-Oriented Analysis and Design framework was chosen, and UML diagram models, including use case, activity, and class diagrams, were used. The system flowchart, input/output design, system structure, and database schema were also described.

In Chapter Four, the implementation of the system is discussed. Implementation process, development environment, and software used to develop the system, which include Python programming language, Flask framework, OpenCV, YOLOv8, and Scikit-learn are mentioned. Description of data sets, including fifty videos of cattle movements, as well as feature extraction and classification, is provided. The system was implemented as a live web application allowing farmers to input videos, get automatic lameness predictions, and access the health history of their cattle. Gait analysis was able to provide tracking-based features and classify each animal into Normal or Suspected Lameness classes, which proved that this method can be used as an affordable decision-making aid.

### 5.3 Conclusion

In conclusion, the success of this project in developing a novel, low-cost, and efficient system for lameness detection among cattle using video-based AI is highlighted. The system fulfilled its intended purpose by developing an efficient video-based lameness detection system for cattle using an AI-based approach. The system fulfilled all four specific objectives of this research project, including the creation of a web platform where videos can be uploaded, the identification of relevant motion-based features such as stride length, walking speed, and movement symmetry, training of an SVM model, and developing a history dashboard.

It shows that the use of motion-based AI lameness detection is not only possible but also feasible since even motion-based systems like this one require no special hardware or sensors and can be easily used by smallholder cattle farmers in developing countries without spending much money. Although the system presented here is just the proof-of-concept of what a lameness detection system based on deep neural network algorithms might look like, it forms a good starting point for further development.

### 5.4 Recommendations

- Dataset Expansion: For future studies, it is recommended that a much bigger set of video datasets of cattle movement be gathered and used for analysis purposes. This will contribute towards a more generalised approach of classification and increased precision rate.
- Deep Learning Integration: Rather than using the current classifier algorithm based on the use of the SVM technique, deep learning algorithms can be employed to help the system learn the complex spatiotemporal aspects of gait automatically, resulting in accuracy of above 90%, which is in line with modern literature.
- Multi-Language Support: For better integration into the communities where the system is supposed to be deployed, it may be beneficial to include support for various languages spoken in these areas.
- Veterinary Alert System Integration: Another recommendation would be to incorporate an alert system to automatically notify veterinarian services upon detection of lameness in animals.
- Real-Time Video Processing: Real-time video streaming analysis should be incorporated into the existing batch-upload framework, ensuring real-time monitoring of animal movement without the need for manual upload of videos.

- Mobile Application Development: Development of an accompanying mobile app could be pursued as a way of improving access among farmers in the field for capturing and analyzing videos using their smartphones instead of browsers on their desktops.
- Transformer-Based Models: Research should focus on transformer-based architecture for computer vision tasks and video processing frameworks trained on large datasets to potentially realize better results than what can be achieved by SVM and CNN frameworks.

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## APPENDICES

### Appendix A: Sample Dataset Structure

The Cattle Lameness Dataset (Sohan et al., 2026) is organised as follows:

- CattleLameness/
- lame/ — 25 short MP4 video clips of lame cattle walking
- normal/ — 25 short MP4 video clips of normal cattle walking

Each video clip is between 5 and 15 seconds in duration, recorded at 24–30 fps under farm conditions. Videos were labelled by veterinary experts as either lame or normal based on clinical locomotion scoring.

### Appendix B: Key Source Code Snippets

Feature Extraction Module (pose_estimator.py and gait_analyzer.py)

def extract_pose_keypoints(video_path, sample_fps=5, min_frames=8): tracks = run_yolov8_tracking(video_path, sample_fps) best_track = select_longest_valid_track(tracks, min_frames) return {"centroids": best_track.centroids, "bboxes": best_track.bboxes}def analyze_gait(pose_data, frame_rate=5): features = extract_gait_features(pose_data, frame_rate) bundle = joblib.load("backend/app/ml/models/cattle_lameness_model.joblib") model = bundle["model"] X = build_feature_vector(features, bundle["feature_cols"]) prediction = model.predict(X)[0] probability = model.predict_proba(X)[0][1] return round(probability * 10, 1), classify_status(prediction, probability)

**SVM Model Training (train_model.py)**

from sklearn.pipeline import Pipelinefrom sklearn.preprocessing import StandardScalerfrom sklearn.svm import SVCfrom sklearn.calibration import CalibratedClassifierCVimport joblib model = Pipeline([ ("scaler", StandardScaler()), ("clf", CalibratedClassifierCV( SVC(kernel="rbf", C=2.0, class_weight="balanced", random_state=42), method="isotonic", cv=3, )),])model.fit(X_train, y_train)joblib.dump({"model": model, "feature_cols": FEATURE_COLS, "classes": ["Normal", "Lame"]}, "cattle_lameness_model.joblib")

**Flask Route for Video Upload and Prediction (app.py)**

@recordings_bp.route("/upload", methods=["POST"])def upload_recording(): file = request.files["video"] validate_video_file(file) recording = save_recording_metadata(file) start_background_analysis(recording.id) return jsonify(recording.to_dict()), 202def run_recording_analysis(app, recording_id): animals_data = track_multiple_blobs(recording.file_path) for animal_id, pose_data in animals_data.items(): lameness_score, status = analyze_gait(pose_data) save_detected_animal(recording_id, animal_id, lameness_score, status)