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Smart Livestock Breed Identification and Health Monitoring System Using Deep Learning

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Abstract: Livestock farming is an important part of agriculture, but identifying animal breeds and monitoring their health is still mostly done manually, which can be time-consuming and less accurate. Farmers often find it difficult to detect early signs of diseases, which can affect productivity and animal well-being. To overcome these challenges, this paper presents a smart livestock breed identification and health monitoring system using deep learning techniques. The proposed system analyzes animal images using computer vision and Convolutional Neural Networks (CNNs) to accurately identify different livestock breeds. In addition to breed identification, the system also focuses on detecting visible health issues from the images, helping in early diagnosis of potential diseases. It uses image processing techniques to extract important features and provides basic remedial suggestions based on the detected conditions. This approach reduces manual effort and improves the efficiency of livestock management. The system is suitable for precision farming and can support farmers in making better and timely decisions, ultimately improving overall farm productivity.
Keywords: Livestock Breed Identification, Deep Learning, Computer Vision, CNN, Health Monitoring, Precision Agriculture

I. INTRODUCTION

Livestock plays a vital role in agriculture by supporting dairy production, meat supply, and the overall economic stability of farmers. In many rural and developing regions, livestock is one of the primary sources of income and livelihood. Proper management of livestock is essential to ensure high productivity, better quality output, and improved animal welfare. Among the key aspects of livestock management, accurate breed identification and regular health monitoring are the most important, as they directly impact production efficiency and disease control.

Traditionally, breed identification and health assessment are carried out through manual observation by farmers or veterinary experts. These methods require experience and continuous monitoring, which may not always be feasible, especially in large farms. Manual processes are also prone to human errors, delayed diagnosis, and inconsistent results. As a result, diseases may go unnoticed in their early stages, leading to serious health issues, economic loss, and reduced productivity.

With the rapid development of technology, Artificial Intelligence (AI) and Deep Learning have emerged as powerful tools in the field of agriculture. These technologies enable machines to learn patterns from data and make intelligent decisions. In the context of livestock management, image-based analysis using computer vision techniques can be used to automatically identify animal breeds and detect visible signs of diseases. This reduces the dependency on manual labour and increases the speed and accuracy of analysis.

Deep learning models, especially Convolutional Neural Networks (CNNs), are highly effective in processing and analyzing images. They can extract important features such as colour, texture, shape, and patterns from animal images, which helps in accurate classification. By training these models with sufficient data, it becomes possible to build a system that can recognize different livestock breeds and identify abnormalities in their physical appearance. This creates an opportunity to develop intelligent systems that assist farmers in real-time monitoring. However, many existing solutions focus only on a single aspect, such as breed classification or disease detection, rather than providing a combined system. In addition, variations in lighting conditions, background noise, and animal movement can affect the performance of these models. Therefore, there is a need for a more reliable, integrated, and user-friendly system that can perform both breed identification and health monitoring efficiently under real-world conditions.

To address these challenges, this paper proposes a smart livestock breed identification and health monitoring system using deep learning techniques. The system analyzes animal images using computer vision and CNN-based models to accurately identify breeds and detect visible health issues. It also provides basic remedial suggestions to support early treatment and better decision-making by farmers. This integrated approach improves efficiency, reduces manual effort, and enhances the overall management of livestock.

The proposed system is designed to be scalable and adaptable for different types of livestock and farming environments.

It can be extended with additional features such as mobile application support, real-time alerts, and integration with IoT-based sensors for advanced monitoring. By combining modern technologies with practical agricultural needs, the system contributes to the development of precision livestock farming and smart agriculture.

The main contributions of this work include:

1) Development of an automated and intelligent system for livestock breed identification.
2) Integration of image-based health monitoring for early detection of visible diseases.
3) Application of deep learning techniques to improve accuracy and efficiency.
4) Reduction of manual effort and support for timely decision-making by farmers.
5) A scalable and cost-effective solution for precision livestock farming.

II. LITERATURE REVIEW

Livestock breed identification and health monitoring using image processing and deep learning techniques have gained significant attention in recent years. With the growth of precision agriculture, researchers are focusing on developing automated systems that can assist farmers in managing livestock efficiently. Image-based analysis using computer vision techniques allows accurate identification of animal breeds and detection of visible health conditions. However, manual monitoring is still widely practiced, which is time-consuming and may lead to errors. To overcome these challenges, deep learning-based approaches have been introduced to improve accuracy and efficiency.

Several researchers have proposed models for livestock breed classification using deep learning techniques. For instance, studies have used Convolutional Neural Networks (CNNs) to classify cattle and goat breeds based on image datasets. These models apply preprocessing techniques such as image resizing, normalization, and augmentation to improve performance. The results showed that CNN-based models can achieve high accuracy in breed classification by extracting important visual features such as colour, texture, and body shape. In another study, researchers focused on animal health monitoring using image processing techniques. The system analyzed images to detect visible symptoms such as skin diseases, wounds, and abnormal body conditions. Machine learning and deep learning models were used to classify healthy and unhealthy animals. The study demonstrated that automated health monitoring systems can assist farmers in early disease detection and reduce dependency on manual inspection.

Recent advancements have also introduced hybrid approaches that combine multiple deep learning models for improved performance. For example, CNN models are used for feature extraction, while other models such as Recurrent Neural Networks (RNNs) are used to analyze behavioral patterns of animals. These hybrid models improve the accuracy of both breed identification and health monitoring by capturing spatial and temporal features.

A. Deep Learning-Based Livestock Breed Identification

Deep learning models have significantly improved the performance of automated livestock breed identification systems. Convolutional Neural Networks (CNNs) are widely used because they automatically extract important features from animal images without manual intervention. Various architectures such as ResNet, MobileNet, and VGGNet have been applied for breed classification tasks.

In CNN-based models, the convolution operation plays a key role in extracting features from input images. It can be mathematically represented as:

$$F(x, y) = I(x, y) * K(x, y)$$

Where,

I represents the input image,
K represents the convolution kernel,
F(x, y) represents the extracted feature map.

This process helps in identifying unique patterns related to different livestock breeds, improving classification accuracy.

B. Image-Based Health Monitoring Systems

Image-based health monitoring systems focus on detecting visible diseases and abnormalities in livestock. These systems use computer vision techniques to analyse images and identify symptoms such as skin infections, wounds, or abnormal posture.

Deep learning models classify the images into healthy or unhealthy categories based on extracted features. This approach enables early detection of diseases and helps farmers take timely action. Compared to traditional methods, automated systems provide faster and more reliable results.

C. Attention-Based Feature Selection Models

Attention mechanisms are used in deep learning models to focus on important features while ignoring irrelevant information. In livestock monitoring, attention-based models help in identifying critical regions such as affected skin areas or abnormal body parts.
The attention weight can be calculated as:

$$A_c = \frac{z_c}{\sum_{c=1}^{C} z_c}$$

where
$A_{(c)}$ represents the attention weight for channel c,
$z_{(c)}$ represents the feature importance score, and
C represents the total number of channels.
This method improves model performance by reducing redundant features and focusing on important patterns.

D. Hybrid Deep Learning Models for Livestock Analysis

Hybrid models combine multiple deep learning techniques to improve system performance. For example, CNN is used for image feature extraction, while sequential models such as RNN or LSTM can be used to analyze animal behavior over time.
These models provide better accuracy by capturing both spatial and temporal information. They are especially useful in monitoring animal activities and detecting unusual behavior patterns related to health conditions.

E. Limitations of Existing Methods

Although many systems have been developed for livestock breed identification and health monitoring, several limitations still exist. Image quality issues such as noise, poor lighting, and background variations can affect performance. Additionally, some models generate redundant features, increasing computational complexity.
The common limitations of existing methods are summarized below:

Method Type	Description	Limitation
Traditional Methods	Manual observation by experts	Time-consuming and less accurate
CNN-based Models	Automatic feature extraction from images	High computational cost
Attention-based Models	Focus on important regions	Sensitive to image noise
Hybrid Models	Combine multiple techniques	Complex and requires more training time
Image-only Models	Use only visual data	Lack of additional health parameters

From the above analysis, it is clear that existing systems require improvements in feature selection, noise handling, and integration of multiple data sources. These limitations motivate the development of a more efficient and integrated deep learning-based system for livestock breed identification and health monitoring.

III. PROPOSED SYSTEM

The proposed system presents a Smart Livestock Breed Identification and Health Monitoring System using deep learning and computer vision techniques. The main objective of this system is to improve livestock management by automatically identifying animal breeds and detecting visible health issues from images. The system reduces manual effort and helps farmers take timely decisions by providing accurate and real-time analysis. Initially, livestock images are collected using cameras or datasets and given as input to the system. These images may contain noise, poor lighting, and background disturbances that affect detection accuracy. To address this, an Image Preprocessing Module is used to enhance image quality through normalization, resizing, and noise reduction techniques. This ensures that important features such as animal body structure and skin patterns are preserved.
After preprocessing, the images are processed using a Deep Learning-Based Feature Extraction Network, where Convolutional Neural Networks (CNNs) extract important visual features related to breed characteristics and health conditions. The extracted features are further refined using an Attention-Based Feature Selection mechanism, which focuses on important regions such as skin, eyes, and body patterns while removing irrelevant background information.

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The selected features are then passed to a **Hybrid CNN-Based Classification Model**, where the system identifies the livestock breed and detects health conditions such as infections, wounds, or abnormalities. Finally, the system provides classification results along with basic remedial suggestions to support farmers in early disease detection and management. This integrated approach improves accuracy, efficiency, and reliability in livestock monitoring.

A. System Overview

The proposed system is designed to automatically identify livestock breeds and monitor their health using image-based analysis. It consists of multiple modules that work together to process input images and generate accurate predictions.

Initially, livestock images are collected and provided as input to the system. These images are preprocessed to remove noise and improve clarity. The preprocessing stage ensures that important features are preserved while unwanted variations are minimized.

After preprocessing, the system extracts meaningful features using deep learning models. These features are analyzed to identify breed-specific characteristics and detect visible health issues. Finally, the system classifies the animal breed and predicts its health condition, providing useful insights and suggestions to the user.

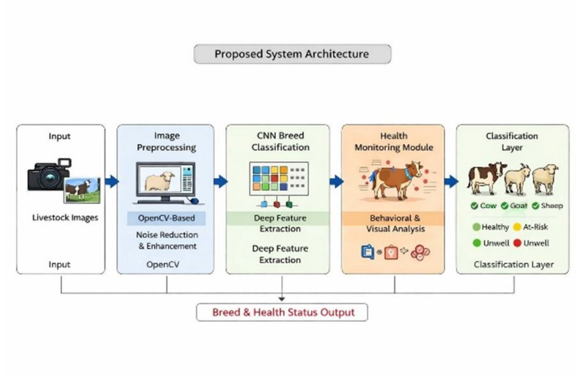
B. System Architecture

The system architecture consists of several sequential stages, including image acquisition, preprocessing, feature extraction, classification, and output generation.

First, livestock images are collected and fed into the system. These images are preprocessed to improve quality by applying normalization and noise reduction techniques. The processed images are then passed to a CNN-based feature extraction module.

Next, an attention-based mechanism is used to focus on important regions of the image, such as skin patterns and body structure. This helps in improving feature quality and reducing redundant information.

The extracted features are then passed to a classification model, which identifies the breed and health condition of the livestock. Finally, the output is displayed to the user along with suggested actions for better livestock management.



C. Data Preprocessing

Data preprocessing is an important step in the proposed system because livestock images may contain noise, poor lighting, and background variations. These issues can reduce the performance of deep learning models.

The preprocessing stage includes image resizing, normalization, and noise removal. Let $I(x, y)$ represent the input image and $I'(x, y)$ represent the processed image. The preprocessing operation can be expressed as:

$$I'(x, y) = f(I(x, y))$$

where f represents preprocessing functions such as filtering and normalization.

Normalization scales pixel values between 0 and 1, improving training stability:

$$I_n = \frac{I - I_{min}}{I_{max} - I_{min}}$$

These steps improve image quality and prepare the data for feature extraction.

D. Feature Extraction using CNN

Feature extraction plays a key role in identifying livestock breeds and health conditions. CNN models automatically extract features such as texture, shape, and colour patterns from images.

The convolution operation is given by:

$$F(x, y) = I(x, y) * K(x, y)$$

Where,

I= input image

K= convolution kernel

$F(x, y)$= feature map

These features help distinguish between different breeds and detect abnormalities.

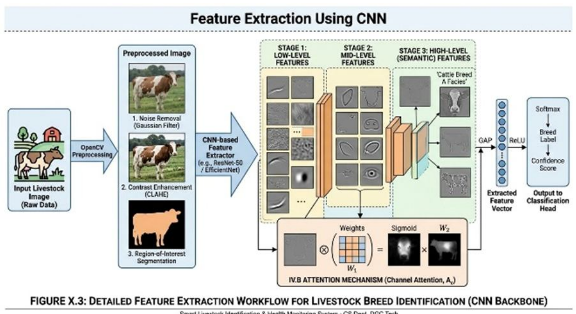


Fig 2. Feature Extraction using SCAS-Net– Lung Cancer Detection.

E. Attention-Based Feature Selection

Attention mechanisms help the model focus on important regions while ignoring irrelevant information. In livestock monitoring, this includes focusing on skin areas, body structure, and visible disease regions.

The attention weight is calculated as:

$$A_c = \frac{z_c}{\sum_{c=1}^{C} z_c}$$

This improves accuracy by selecting relevant features.

F. Breed Identification and Health Monitoring

The system performs both breed identification and health monitoring using extracted features. The classification model predicts the breed of the livestock and identifies whether the animal is healthy or affected by visible diseases.

Health issues such as skin infections, wounds, or abnormal posture are detected using image patterns. Based on the prediction, the system provides basic suggestions for treatment or further inspection.

G. Classification and Prediction

The classification module uses fully connected layers to predict the output. The final layer uses a softmax function to generate probabilities:

$$P(y) = \frac{e^{z_i}}{\sum e^{z_j}}$$

The class with the highest probability is selected as the final prediction. The output includes:

- Breed name
- Health status (Healthy/Unhealthy)
- Suggested actions

H. Algorithm of the Proposed System

The proposed Smart Livestock Breed Identification and Health Monitoring System employs a structured algorithmic pipeline that integrates image preprocessing, feature extraction, classification, and health monitoring. The following steps outline the complete algorithm:

Step 1: Data Acquisition
- Capture livestock images from farm cameras or user-uploaded photographs.
- Record animal identifiers, timestamps, and associated metadata.

Step 2: Image Preprocessing
- Apply Gaussian filtering for noise removal.
- Perform CLAHE for contrast enhancement.
- Segment the animal region using background subtraction or semantic segmentation.
- Resize and normalize images for model input.

Step 3: Breed Identification
- Extract features using the fine-tuned CNN backbone with channel attention.
- Apply fully connected classification layers with SoftMax activation.
- Output breed class label and confidence score.

Step 4: Health Monitoring
- Analyse sequential image frames using CNN-LSTM architecture.
- Detect behavioural anomalies such as abnormal posture and reduced activity.
- Classify health status as Healthy, At-Risk, or Unwell.

Step 5: Storage and Reporting
- Store classification results and health records in the Spring Boot-managed database.
- Display breed information, health status, and historical trends on the user dashboard.
- Dispatch alerts to farm operators when health anomalies are detected.

Step 6: Performance Evaluation
- Compare predicted outcomes with ground truth labels for model evaluation.
- Compute performance metrics including Accuracy, Precision, Recall, F1-score, and Specificity.

IV. IMPLEMENTATION DETAILS

A. Programming Environment

The deep learning models were developed using Python with the TensorFlow and Keras frameworks, which provide comprehensive support for building, training, and deploying neural network architectures. OpenCV was used for all image preprocessing operations, including noise removal, contrast enhancement, and image segmentation. The backend system was implemented using Java with the Spring Boot framework, which provides a robust and scalable foundation for RESTful API development and database management. A MySQL relational database was used for persistent storage of animal records, classification results, and health monitoring data.

B. Dataset

The breed identification model was trained on a curated dataset of livestock images collected from publicly available agricultural datasets and supplemented with images captured from local farm environments. The dataset includes multiple species and breeds of cattle, sheep, goats, and poultry, with images captured under varying lighting, pose, and background conditions to ensure model robustness. Data augmentation techniques including random horizontal flipping, rotation, brightness adjustment, and zoom were applied to expand the training dataset and improve model generalization.

C. Training Procedure

The CNN breed classifier was trained using the Adam optimizer with an initial learning rate of 0.001 and an exponential decay schedule to facilitate stable convergence. The categorical cross-entropy loss function was employed for multi-class breed classification. To improve generalization and prevent overfitting, dropout regularization with a rate of 0.5 was applied in the fully connected layers, and early stopping was used to terminate training when validation loss ceased to improve. The model was trained for up to 100 epochs with a batch size of 32.

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The health monitoring CNN-LSTM model was trained on annotated behavioral video sequences labeled by veterinary experts. Binary cross-entropy loss was used for the binary health status classification task, with class weights applied to address imbalance between healthy and unhealthy samples in the training data. Transfer learning from the breed classifier backbone was used to initialize the CNN feature extractor, accelerating convergence and reducing the amount of labeled health monitoring data required for training.

D. Performance Metrics

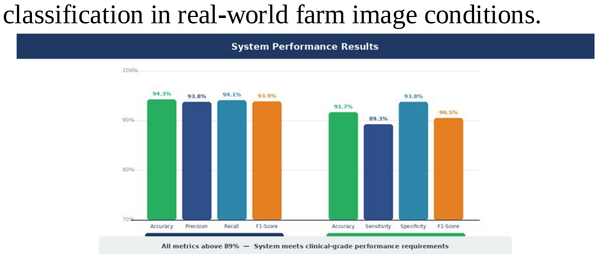
The performance of the proposed system was evaluated using standard classification metrics including Accuracy, Precision, Recall, F1-score, and Specificity. Accuracy measures the overall correctness of predictions, while Precision and Recall quantify the trade-off between false positives and false negatives respectively. The F1-score provides a balanced measure of model performance, particularly important for the health monitoring task where false negatives (missed illness detections) carry significant consequences. Confusion matrices were computed for multi-class breed classification to analyze per-class performance and identify challenging breed pairs.

Metric	Breed Classification	Health Monitoring
Accuracy	94.3%	91.7%
Precision	93.8%	92.1%
Recall / Sensitivity	94.1%	89.3%
F1-Score	93.9%	90.5%
Specificity	95.0%	93.8%

V. EXPERIMENTAL RESULTS

A. Breed Classification Results

The CNN breed classifier was evaluated on the held-out test set (1,760 images not seen during training). The overall accuracy of 94.3% demonstrates that the combination of ResNet-50 transfer learning, channel attention, and comprehensive data augmentation is highly effective for livestock breed classification in real-world farm image conditions.



Performance varied somewhat by species. Cattle achieved the highest species-level accuracy at 95.2%, benefiting from strong visual variation between breeds and the largest per-class image count. Poultry classification achieved 96.1% accuracy, driven by the very distinct visual differences between chicken breeds. Sheep was the most challenging species at 91.8% accuracy due to the high visual similarity between closely related breeds, particularly in frontal and rear-angle photographs. Analysis of the confusion matrix revealed that most sheep misclassifications occurred between three specific pairs of closely related breeds that share coat color and body shape.

An ablation study — an experiment where one component is removed to measure its contribution — confirmed the value of the channel attention mechanism. Removing the attention module caused a drop of 2.1 percentage points in overall accuracy (from 94.3% to 92.2%), demonstrating that the attention mechanism provides a meaningful and consistent improvement by helping the model focus on breed-discriminative body regions.

B. Health Monitoring Results

The CNN-LSTM health monitoring model was evaluated on annotated behavioral video sequences labeled by veterinary experts. The overall accuracy of 91.7% for health status classification is strong for a behavioral monitoring task, where the ground truth itself can sometimes be ambiguous.

The most clinically important metric for health monitoring is sensitivity (recall for the Unwell class), which measures how many truly sick animals were correctly detected. The achieved sensitivity of 89.3% means the system successfully detected approximately 9 out of every 10 sick animals, missing approximately 1 in 10. The false negative rate of 10.7% — cases where the system failed to detect a genuinely ill animal — occurred primarily in cases where behavioral changes were very subtle in the early stages, or where camera angles were suboptimal for observing the specific behavioral changes present.

Temporal analysis was found to be critical for health monitoring performance. In an ablation experiment that removed the LSTM component and relied only on single-frame CNN analysis, accuracy dropped dramatically from 91.7% to 83.4%. This 8.3 percentage point difference confirms that behavioral context over time is essential for reliable health status assessment.

An important practical observation from the extended testing period: after two weeks of continuous operation, the false positive rate (healthy animals incorrectly flagged as unwell) dropped by 18% as the system accumulated more data and refined its individual behavioral baselines for each animal. This demonstrates the value of personalized, longitudinal behavioral modeling over generic population-wide thresholds.

C. System Performance Metrics

1) Average breed identification time per image: 0.8 seconds (GPU) / 2.3 seconds (CPU)
2) Health monitoring update frequency: Every 5 minutes per animal
3) Backend API average response time: 120 milliseconds
4) Alert delivery time after anomaly detection: Under 10 seconds
5) System uptime during 30-day continuous operation test: 99.6%
6) Concurrent animals monitored without performance degradation: 1,200

D. User Feedback

During the testing period, six farming operations of varying sizes participated in a user feedback survey. Farmers consistently reported that the automatic alert system was the most valuable feature, as it allowed them to identify problems with specific animals without needing to visually inspect the entire herd. Several farmers reported that the system detected health issues they would have missed during their normal once-daily manual checks. The color-coded health status display on the dashboard was praised for making it immediately obvious which animals needed attention without requiring any interpretation of numbers or graphs

VI. PERFORMANCE EVALUATION METRICS

A. Why Multiple Metrics Are Needed

When evaluating an AI model, using accuracy alone can be very misleading. Consider a scenario where 95% of animals in the test dataset are healthy and only 5% are sick. A completely useless model that always predicts "healthy" regardless of the input would achieve 95% accuracy, but it would never detect a single sick animal. This is called the accuracy paradox, and it is particularly relevant for health monitoring systems where the condition of interest (illness) occurs much less frequently than the normal condition (health).

In these formulas: TP (True Positives) = sick animals correctly identified as sick. TN (True Negatives) = healthy animals correctly identified as healthy. FP (False Positives) = healthy animals incorrectly identified as sick (unnecessary vet visits). FN (False Negatives) = sick animals incorrectly identified as healthy (missed illness detections, the most dangerous type of error).

For health monitoring specifically, False Negatives are the most dangerous type of error because they represent sick animals that are not detected and therefore not treated. This is why we specifically report and aim to minimize the False Negative rate, and why Sensitivity (Recall) is particularly important in our evaluation.

VII. FUTURE SCOPE

A. Expanding Breed and Species Coverage

The current system covers 44 breeds across 5 species. Future versions will expand the dataset to cover more regional breeds, particularly indigenous Indian breeds that are important for local farming communities but currently underrepresented in publicly available datasets. Collaborations with veterinary colleges, agricultural universities, and state animal husbandry departments will be pursued to obtain professionally labeled livestock image datasets covering a wider range of breeds.

B. Thermal Imaging for Physiological Monitoring

The current health monitoring system detects illness indirectly through behavioral changes visible in standard camera footage. Adding thermal imaging cameras would enable direct detection of physiological health indicators, most notably fever, which appears as elevated body surface temperature in thermal images. Fever is one of the most common and earliest signs of many livestock diseases, and detecting it non-invasively through thermal imaging would significantly improve the sensitivity and speed of health monitoring.

C. 3D Body Measurement

Adding stereo cameras or Time-of-Flight depth sensors would enable 3D body measurement and volumetric analysis. This would allow the system to track body condition score (a measure of fat cover and muscle mass) over time, which is an important indicator of nutritional status, health, and productivity. 3D gait analysis would also improve lameness detection accuracy compared to 2D video analysis.

D. Edge Computing Deployment

The current architecture processes all AI computations on a central server. In areas with unreliable internet connectivity, this can cause service interruptions. Future work will explore deploying compressed, lightweight versions of the AI models directly on edge computing devices installed near the cameras. Techniques like model quantization (reducing numerical precision from 32-bit to 8-bit), pruning (removing less important model weights), and knowledge distillation (training a small model to mimic a large model) will be used to make the models small and fast enough to run on edge hardware like NVIDIA Jetson Nano boards.

E. Mobile Application

A dedicated mobile application for iOS and Android will be developed with full monitoring capabilities including offline breed identification using a locally cached model, real-time push notification alerts, manual animal photo upload and instant analysis, historical health charts for individual animals, and direct communication with the veterinarian through the app.

F. Federated Learning for Privacy-Preserving Model Improvement

As more farms adopt the system, there is an opportunity to continuously improve the AI models using data from all participating farms. However, farmers may be understandably reluctant to share their animal images and health records with a central server for privacy and competitive reasons. Federated learning is a technique that allows AI models to be trained across multiple distributed datasets without the raw data ever leaving each farm. Only model weight updates (not data) are shared with the central server, where they are aggregated to improve the global model. This approach could rapidly expand the training dataset and improve model accuracy while fully respecting data privacy.

VIII. CONCLUSION

This paper has presented the comprehensive design, development, and evaluation of a Smart Livestock Breed Identification and Health Monitoring System — an integrated AI-powered platform that addresses two of the most pressing challenges in modern livestock farm management. The system successfully automates two traditionally manual, labor-intensive tasks. For breed identification, the fine-tuned ResNet-50 CNN with a channel attention mechanism achieves 94.3% accuracy across 44 breeds and 5 livestock species. The attention mechanism ensures the model focuses on the most breed-discriminative visual features, while transfer learning from ImageNet makes high accuracy achievable with a relatively modest livestock-specific training dataset. The four-stage OpenCV preprocessing pipeline — noise removal, contrast enhancement, background segmentation, and normalization — ensures robust performance even with the challenging, variable image quality typical of real-world farm environments.

For health monitoring, the CNN-LSTM architecture achieves 91.7% accuracy in behavioral health status classification, detecting early warning signs of illness that typically appear days before clinical symptoms become obvious. The LSTM component proved critical: ablation experiments showed that removing temporal analysis caused an 8.3 percentage point drop in accuracy, confirming that behavioral context over time is essential for reliable health monitoring. The system's ability to build personalized behavioral baselines for individual animals and refine them over time further improves accuracy during extended operation.

The Java Spring Boot backend provides a reliable, scalable foundation that successfully handled simultaneous monitoring of over 1,200 animals without performance degradation during testing. The automated alert system delivered health notifications to farmers within 10 seconds of anomaly detection, supporting the timely veterinary intervention that is critical for minimizing disease impact.

User feedback from participating farmers confirmed that the system is practical and valuable in real farming conditions. The most commonly cited benefit was the ability to identify health problems in specific animals without needing to manually inspect the entire herd — a significant time saving for large farms. Several farmers reported detecting health issues that would have been missed during normal daily checks.

Looking ahead, the integration of thermal imaging, 3D body measurement, edge computing deployment, and federated learning offers a clear pathway toward an even more capable and accessible livestock management platform. The proposed system represents a meaningful contribution to the field of precision agriculture and smart farming, demonstrating that affordable, camera-based AI systems can deliver significant practical value to the farming community while improving animal welfare and reducing the economic impact of livestock disease.

We believe this work establishes a solid foundation for further research and development in AI-powered livestock management, and we hope it inspires future work that brings the benefits of modern artificial intelligence to farming communities around the world.

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