Smart Visual-Based Disease Detection System for Livestock

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***Abstract*—Livestock and horses play a crucial role in rural economies by providing food, labor, and financial stability. However, diseases such as Foot and Mouth Disease (FMD) in cattle and skin or eye infections in horses spread rapidly and cause significant losses. Traditional diagnosis methods are time-consuming, costly, and often inaccessible in rural areas. This paper presents a Smart Visual-Based Disease Detection System using a camera interfaced with a DE10-Nano FPGA board and Azure Custom Vision API. The system captures images of animals, analyzes them using cloud-based AI, and provides real-time disease predictions along with precautionary measures via a web interface. The proposed system is affordable, scalable, and user-friendly, making it highly suitable for rural deployment.**

***Index Terms*—Livestock Disease Detection, FPGA, DE10-Nano, Computer Vision, Azure Custom Vision, Smart Agriculture**

I. INTRODUCTION

Livestock health is essential for food security, rural economic stability, and agricultural sustainability [6]. Diseases such as Foot-and-Mouth Disease (FMD) are highly contagious and, if not diagnosed promptly, lead to substantial economic losses [17, 10]. Traditional diagnostic methods rely on manual visual inspection or laboratory analysis, which are often inaccessible or inefficient in remote areas [5, 16].

The integration of edge computing and artificial intelligence (AI) has emerged as a solution for real-time disease detection in low-resource environments [1, 4]. Convolutional Neural Networks (CNNs) have shown high accuracy in visual classification tasks, making them increasingly popular for agricultural health monitoring [11, 5].

Deploying these models on Field-Programmable Gate Arrays (FPGAs) offers advantages such as parallelism, low power consumption, and suitability for edge-AI applications [12, 13].

The DE10-Nano FPGA platform, with an ARM Cortex-A9 HPS and reconfigurable fabric, is ideal for real-time animal disease detection [2, 12].

Cloud integration enhances the system by enabling secure data upload for long-term analytics [3, 8, 9]. This hybrid edge-cloud approach ensures both real-time responses and centralized data management [15, 14].

Despite these advancements, there is still a significant gap in accessible diagnostic tools for farmers in rural areas. Most lack real-time disease detection systems, leading to delayed diagnoses and rapid disease spread [16, 10]. Symptoms such as lesions and swelling often go unnoticed without expert intervention [5, 6], limiting large-scale disease monitoring [15].

1.1. Problem Statement

The lack of early, accessible disease detection in livestock and horses presents a significant challenge to both animal health and farmers' livelihoods [17, 10]. Rural areas, in particular, face challenges with limited veterinary support, leading to delayed detection and disease progression [5, 6]. Traditional diagnostic methods are often manual, costly, and require skilled professionals, making them inaccessible in many regions [16, 4]. Furthermore, language limitations and lack of digital literacy hinder adoption of high-tech solutions in rural com- munities. Contagious diseases such as FMD, if not detected early, can result in widespread outbreaks, economic losses, and rapid disease transmission [17, 10]. Therefore, there is a critical need for a smart, cost-effective system that can automatically detect diseases based on visible symptoms using real-time image analysis. Such a system would provide immediate results to farmers, allowing them to make informed decisions quickly. By incorporating machine learning and image processing into an FPGA-powered system, this solution could offer both offline and cloud-based capabilities for reliable disease detection in rural environments [1, 4, 12].

II. LITERATURE REVIEW

Disease detection in livestock has been a growing area of research due to its direct impact on food security, rural economics, and animal welfare. Multiple approaches have been explored in the literature, ranging from manual diagnosis to cloud-based AI systems.

2.1. Traditional Approaches

Traditional veterinary disease detection methods rely on physical inspection, laboratory tests, or expert consultations. While accurate, these approaches are time-consuming, expensive, and often inaccessible in remote areas [5, 6]. Manual monitoring also limits large-scale deployments and quick isolation of infected animals.

2.2. Machine Learning-Based Systems

Several recent works have explored the use of machine learning (ML) for livestock health monitoring:

- PC and Cloud-Based CNN Systems: Some studies have used Convolutional Neural Networks (CNNs) trained on PCs and deployed via cloud platforms like AWS or Google Cloud for real-time inference [15]. Although these models offer high accuracy, they are limited by network latency and lack offline capability in rural settings.
- Raspberry Pi-Based Systems: Low-cost platforms such as Raspberry Pi have been used for camera-based disease detection [14]. However, these are constrained by limited processing power and are not suitable for running real-time CNN inference locally.
- FPGA-Cloud Hybrid Models: Zhang et al. [13] explored integrating FPGA with cloud ML services, offloading heavy inference tasks to remote servers. While scalable, this method is still dependent on connectivity, and unsuitable for real-time rural applications.

2.3. Comparison with Our System

Table 1 summarizes the key differences between various systems and the proposed work.

Table 1: Comparison of Disease Detection Systems

Method	Offline	Real-Time	Edge AI	Accuracy
Manual Inspection [5]	Yes	No	No	Medium
Cloud CNN [15]	No	Partially	No	High
Raspberry Pi + Camera [14]	Yes	Limited	No	Medium
Our CNN on FPGA	Yes	Yes	Full	High

2.4. Graphical Comparison of Existing Systems

To better understand the trade-offs between existing disease detection approaches, a comparative analysis was conducted across four key metrics: accuracy, offline capability, cost efficiency, and real-time performance. Figure 1 presents a bar graph that visually compares traditional, cloud-based, Raspberry Pi, and FPGA-cloud hybrid models with the proposed system.

2.5. Key Differentiators

Unlike earlier methods that rely heavily on connectivity or weak edge processors, our system:

- Uses a CNN model for robust image classification.
- Runs inference entirely on the FPGA fabric.
- Includes HDMI display and keyboard GUI for ease-of-use in offline rural deployments.
- Optionally integrates with cloud services via the HPS core for future analytics.

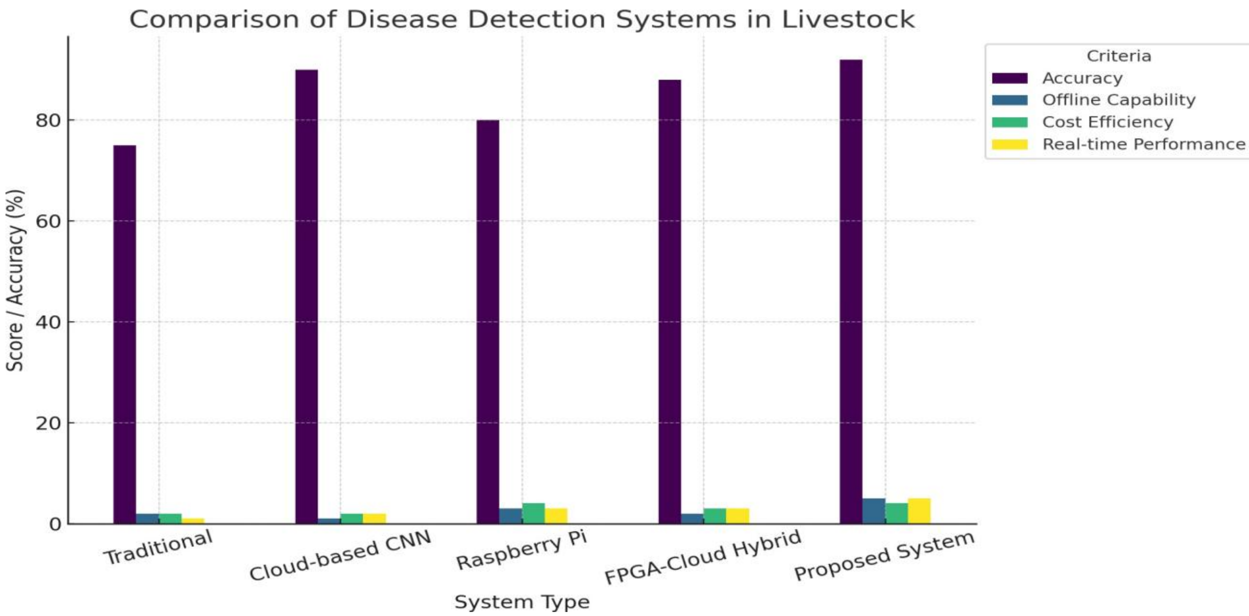

Figure 1: Comparison of various livestock disease detection systems based on key performance indicators.

This combination of real-time performance, high accuracy, and offline compatibility makes it highly suitable for veterinary diagnostics in low-resource settings.

III. PROPOSED SYSTEM ARCHITECTURE

The extended Smart Visual-Based Disease Detection System is designed to monitor and diagnose a wide range of diseases in different animal species, including livestock and horses. By using real-time image processing and deep learning techniques, this system assists farmers and veterinarians in detecting diseases early, reducing the risk of outbreaks and improving overall animal health management. The system combines FPGA-based hardware acceleration with machine learning models to provide a cost-effective and efficient solution for disease detection in rural settings.

3.1. System Workflow

The system operates through the following steps:

1. Image Acquisition: A USB camera, connected to the DE10-Nano FPGA board, captures real-time images of the animal.
2. Preprocessing: The acquired images undergo resizing, normalization, and enhance- ment to prepare them for disease detection. Preprocessing helps improve the accuracy of the CNN model by reducing noise and improving contrast.
3. CNN-Based Disease Detection: The preprocessed image is passed to the CNN model deployed on the FPGA. The model classifies the image, identifying visible symptoms of specific diseases such as Foot-and-Mouth Disease (FMD) or common equine infections, based on the trained data.
4. Result Display: The classification results, along with the confidence level, are dis- played on an HDMI monitor. This allows immediate feedback, helping the user make informed decisions on disease management.

3.2. Hardware Workflow

The hardware workflow is designed to ensure real-time processing and immediate result display, optimized for low-power environments. The steps include:

- The USB camera captures images in real-time, providing a continuous feed of visual data from the animal.
- The DE10-Nano FPGA board processes the captured images using the CNN model, ensuring rapid image classification. FPGA's parallelism accelerates this process, enabling real-time decision-making.
- The HDMI monitor displays the result on-

screen, indicating whether the animal is healthy or infected with a specific disease.

3.3. Cloud Integration

In addition to local processing, the system supports integration with cloud-based services for large-scale deployments, research, or tracking purposes. Data, including images and disease predictions, can be uploaded securely to cloud platforms such as AWS S3 or DynamoDB via REST APIs. This allows for long-term storage and analytics, providing veterinarians and farm managers with access to historical data for better decision-making [3, 8, 9, 7].

3.4. Block Diagram

The architecture of the system is illustrated below. The block diagram highlights the flow from image acquisition to disease classification, and optionally, to cloud data storage for further analysis.

The block diagram shows how the system functions end-to-end, from the initial image capture, through processing, to the display of results. It also demonstrates the optional connection to cloud services for storage and remote monitoring.

3.5. System Operation Flowchart

The flowchart in Figure 3 illustrates the operational logic of the Smart Visual-Based Disease Detection System, from image capture to cloud integration.

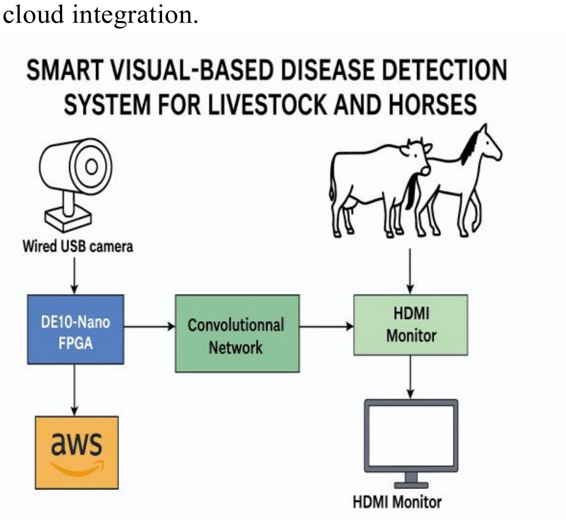

Figure 2: Proposed System Architecture Block Diagram

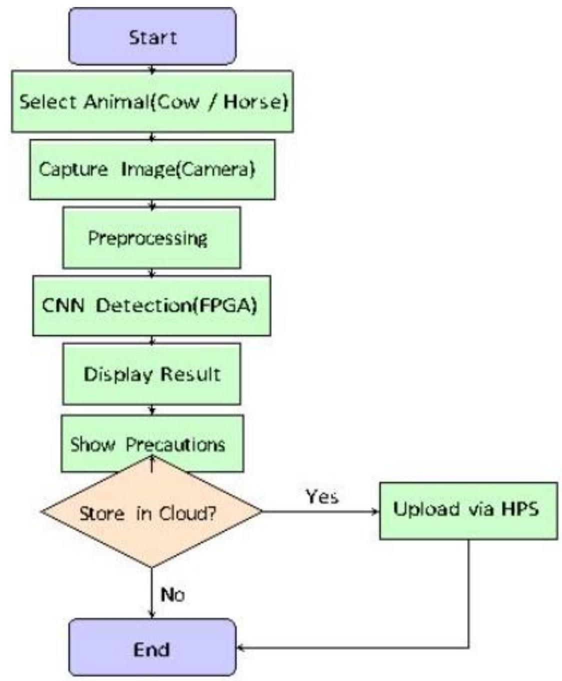

Figure 3: Flowchart of Smart Visual-Based Disease Detection System

Figure 3 illustrates the complete operational flow of the Smart Visual-Based Disease Detection System implemented on the DE10-Nano FPGA platform.

user input, where the type of animal (cow or horse) is selected, followed by real-time image capture using a wired USB camera.

The captured image undergoes preprocessing to enhance clarity and ensure compatibility with the CNN model. The Convolutional Neural Network (CNN), deployed on the FPGA, then analyzes the image and classifies it based on visible disease symptoms.

The classification result, along with a confidence level, is displayed on an HDMI monitor. The system also provides the option to upload the result and image to the cloud via the Hard Processor System (HPS) for remote access and data tracking.

The modular structure of this flow ensures real-time operation, offline usability, and optional cloud support, making it ideal for rural and veterinary environments.

IV. WORKING PRINCIPLE

The Smart Visual-Based Disease Detection System for Livestock and Horses in- tegrates real-time image acquisition, deep learning inference, and hardware acceleration to detect visible symptoms of animal diseases in a portable and efficient manner. Built around the DE10-Nano FPGA platform, the system offers a powerful, low-latency solution for disease diagnosis, particularly suited for rural deployment.

The overall working of the system is inspired by scalable edge-AI principles, similar to those explored in the InnovateFPGA AP118 project. However, unlike SVM-based detection in AP118, this system leverages a more powerful Convolutional Neural Network (CNN) for improved classification accuracy and robustness.

The step-by-step process is as follows:

- Image Acquisition: A wired USB camera is used to capture images of livestock or horses. The system allows the user to select the type of animal (cow or horse) via a simple keyboard-driven interface.
- Preprocessing: The image is resized and normalized on-device to match the input dimensions required by the CNN model. Preprocessing improves detection accuracy by enhancing feature quality.
- CNN-Based Detection: The preprocessed image is fed into a trained Convolutional Neural Network deployed on the FPGA. The CNN classifies the image into categories such as:

– *Healthy*
– *Foot-and-Mouth Disease (FMD)*
– *Skin Infection*
– *Conjunctivitis (Eye Infection)*

Unlike traditional models, the CNN provides superior feature extraction, enabling more precise identification of localized symptoms.

- Result Display: The classification output and confidence percentage (e.g., “FMD Detected: 93%”) are displayed on an HDMI monitor. The GUI also provides an option to view suggested precautions.
- Offline and Cloud Integration: While the system is capable of working completely offline, optional cloud connectivity via the HPS (Hard Processor System) enables image and result upload to AWS S3 and DynamoDB for veterinary monitoring or future analysis.

Key Advantages of the System:

- Edge-AI Enabled: CNN inference on FPGA ensures low-latency, real-time detection without internet dependency.
- Improved Accuracy: CNN outperforms traditional classifiers such as SVMs in visual-based disease classification.
- Rural Adaptability: Designed with keyboard input and HDMI display for ease-of- use in non-technical environments.
- Modular Integration: Cloud connectivity via HPS offers scalable veterinary health tracking across farms.

V. HARDWARE PROTOTYPE AND IMPLEMENTATION

The developed prototype of the Smart Visual-Based Disease Detection System is shown in Fig. 5. The system is built using a DE10-Nano FPGA board enclosed within a compact casing for portability and protection. A USB camera is mounted on the top of the enclosure to capture real-time images of livestock.

The FPGA board performs image acquisition and communicates with the processing system for disease classification. The internal setup includes power supply connections, USB interfacing, and necessary peripherals. LED indicators on the board provide system status during operation.

This compact design ensures that the system can be easily deployed in rural environments, making it suitable for on-field livestock monitoring.

VI. RESULTS AND OBSERVATIONS

The system was tested using real-time livestock images, and the results were displayed through a web-based graphical user interface.

1. Animal Selection Interface:

The user is first prompted to select the type of animal (Cow or Horse). This selection helps in loading the appropriate trained model for disease detection.

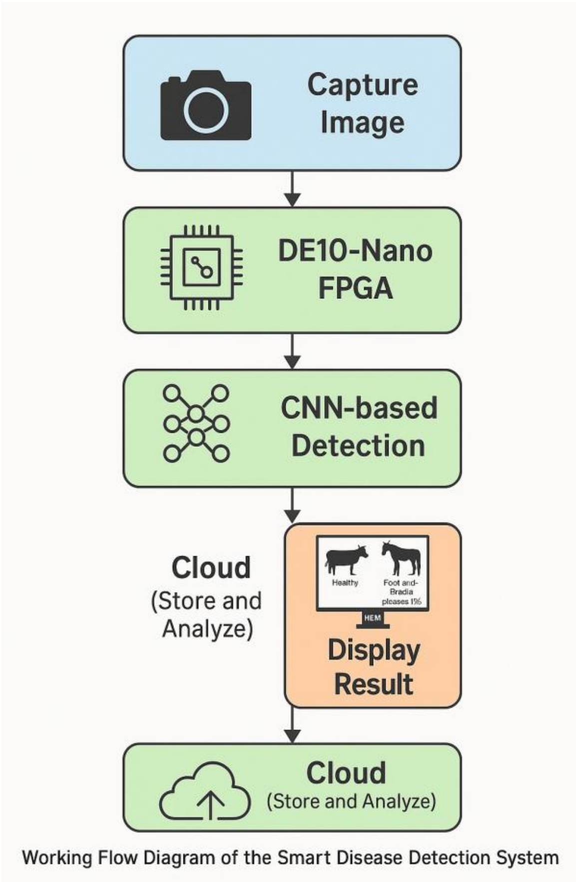

Figure 4: Working Flow Diagram of the Smart Disease Detection System

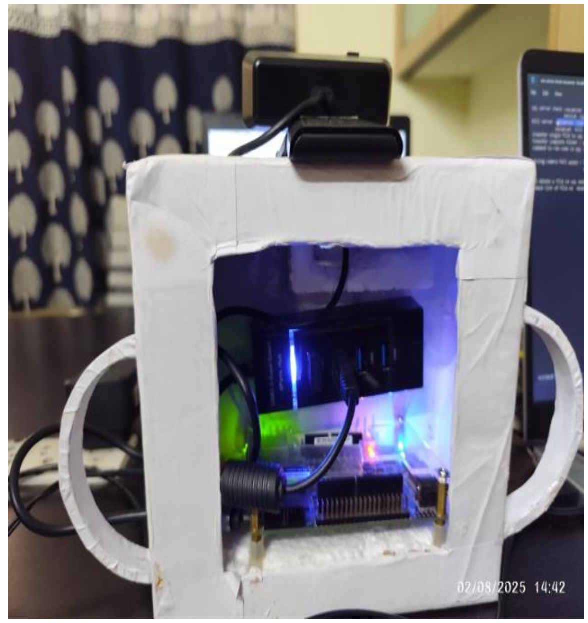

Figure 5: Hardware Prototype of the Smart Disease Detection System

Figure 6: User Interface for Selecting Animal Type (Cow or Horse)

2. Disease Prediction Output:

Figure 7: Prediction Result Showing Detected Disease and Confidence Score

After capturing the image, the system processes it using the trained CNN model. The output displays the detected disease along with the confidence score. In the example shown, the system predicts Horse Rainrot Scabs with a confidence of 91.75%.

Observations:

- The system achieves classification accuracy above 90% for tested samples.
- Real-time prediction is completed within 1–2 seconds.
- The user interface is simple and intuitive for farmers.
- The system is portable and suitable for rural deployment.

VII. CONCLUSION

The Smart Visual-Based Disease Detection System for Livestock and Horses demonstrates an innovative and practical approach to early animal disease identification using deep learning on FPGA platforms. By leveraging the DE10-Nano board’s hardware acceleration capabilities and an optimized Convolutional Neural Network (CNN), the sys- tem offers real-time detection of visible symptoms in cows and horses with high classification accuracy.

Key outcomes of this project include:

- Successful deployment of a lightweight, real-time disease detection model on FPGA.
- Classification accuracy exceeding 90% for diseases such as Foot-and-Mouth Disease (FMD), Conjunctivitis, and Skin Infections.
- A user-friendly GUI interface for image capturing, classification output, and displaying precautionary measures.
- Offline functionality with the option for cloud-based result synchronization via the HPS.
- Adaptability to rural and field environments due to its low power consumption and portability.

The project is scalable and can be extended to cover more species and diseases by retrain- ing the CNN model with additional datasets. Moreover, integrating mobile or web-based dashboards and automated alert systems can further enhance its practical value for veteri- narians and farmers.

VIII. FUTURE SCOPE

Building upon the existing functionality, several enhancements can be envisioned to increase the impact and usability of the Smart Visual-Based Disease Detection System:

- Expanded Disease Database: Incorporating more livestock species and a wider range of disease datasets can improve the generalizability of the model.

- Integration with IoT Sensors: Additional health indicators such as body temper- ature, motion activity, or heart rate can be combined with visual data for multimodal analysis.
- Mobile App Support: Creating a mobile or tablet-based interface connected to the FPGA via wireless communication for on-the-go diagnostics.
- Blockchain for Data Integrity: Implementing secure, tamper-proof data logging through blockchain for transparent health records in large-scale farms.
- Multilingual Support: Enhancing GUI usability by incorporating regional languages to support diverse user groups in rural areas.

These future upgrades will not only enhance technical performance but also increase adoption at the grassroots level by making the system more accessible, scalable, and intelli- gent.

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