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GEN AI DRIVEN LIVE STOCK DISEASE ANALYSIS AND VET CONSULTATION ASSISTANT

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Abstract— **Livestock health issues often go unnoticed until they become severe, leading to significant economic losses and a reduction in farm productivity. To address this critical challenge, the proposed Gen AI Driven Livestock Disease Analysis and Vet Consultation Assistant integrates an advanced dual-LLM (Large Language Model) architecture with Retrieval- Augmented Generation (RAG) for intelligent, explainable disease assessment. Farmers can upload images and descriptive details of affected animals through a mobile or web application. The first LLM processes the inputs to extract essential symptoms and contextual information, while the second LLM performs prompt engineering and retrieves relevant veterinary data from a vector database hosted on the Google Cloud Platform (GCP). Based on the analyzed information, the system predicts probable diseases, recommends preventive and treatment measures, and automatically initiates a veterinarian consultation whenever expert attention is required. Furthermore, the system includes an integrated vaccination alert feature that reminds farmers about scheduled immunizations, thereby preventing potential disease outbreaks. This AI enabled, cloudbased solution ensures faster, accurate, and transparent disease analysis, improving decision-making in livestock health management.**

Index Terms— ***Gen AI, Livestock Disease Analysis, Dual-LLM Architecture, Retrieval-Augmented Generation (RAG), Veterinary Consultation, Symptom Extraction, Disease Prediction, Vector Database, Google Cloud Platform (GCP), Treatment Recommendation, Vaccination Alert System***

I. INTRODUCTION

Livestock farming plays a vital role in ensuring food security, rural employment, and economic sustainability across both developing and developed nations. Healthy livestock populations are essential for maintaining productivity in dairy, poultry, and meat-based agricultural systems. However, livestock health management continues to face significant challenges due to delayed disease detection, limited access to veterinary professionals, and the absence of intelligent decision-support systems, particularly in rural and remote regions. Many livestock diseases remain unnoticed during their early stages, resulting in rapid disease progression, increased mortality rates, and substantial economic losses for farmers.

Traditional livestock disease management relies heavily on manual observation and periodic veterinary visits, which are often insufficient for early diagnosis. Farmers may lack the technical knowledge required to accurately identify disease symptoms, and the availability of trained veterinarians is often constrained by geographic and economic factors. Additionally, conventional systems fail to maintain structured digital health records or provide predictive insights, thereby limiting proactive disease prevention and effective livestock health planning. These limitations highlight the need for an intelligent, scalable, and explainable system capable of supporting farmers in real-time disease assessment and veterinary decision- making.

Recent advancements in Artificial Intelligence (AI), particularly in Machine Learning (ML) and Deep Learning (DL), have demonstrated significant potential in automating disease detection and analysis within the agricultural domain. Image-based disease recognition, predictive modeling, and decision-support systems have been explored in several studies. However, many existing AI-based solutions are limited by single-model architectures, lack of contextual understanding, and poor explainability. Moreover, such systems often operate on static datasets and are prone to hallucinations or inaccurate predictions when deployed in real-world, dynamic environments.

The emergence of Generative Artificial Intelligence and Large Language Models (LLMs) has opened new possibilities for intelligent reasoning, contextual understanding, and natural language interaction. LLMs can process multimodal inputs such as text and images while generating human-readable explanations, making them highly suitable for agricultural advisory systems. Nevertheless, standalone LLMs suffer from limitations such as outdated knowledge, lack of domain specialization, and susceptibility to generating unverifiable responses. To overcome these challenges, Retrieval- Augmented Generation (RAG) has been introduced as a robust framework that enhances LLM outputs by retrieving relevant domain-specific information from external knowledge bases.

In this context, this paper proposes a Gen AI Driven Livestock Disease Analysis and Vet Consultation Assistant, which integrates a dual-LLM architecture with a Retrieval-Augmented Generation (RAG) framework to deliver accurate, explainable, and reliable disease diagnosis for livestock. The proposed system allows farmers to upload images and descriptive information related to affected animals through a web or mobile application. The first LLM focuses on extracting key symptoms, contextual features, and environmental indicators from the provided inputs. These extracted featuresare then converted into embeddings and matched against a domain-specific veterinary knowledge base stored in a vector database hosted on the Google Cloud Platform (GCP).

The second LLM performs advanced reasoning and prompt engineering by combining retrieved veterinary evidence with the extracted symptom data. Based on this analysis, the system predicts probable diseases, recommends preventive and treatment measures, and assesses the severity of the condition. When expert intervention is required, the system automatically initiates a veterinary consultation, thereby bridging the gap between farmers and animal healthcare professionals. Additionally, the system maintains digital health records, vaccination schedules, and alert mechanisms to support proactive livestock management.

The proposed solution is implemented as a cloud- based web and mobile application, leveraging React and React Native for frontend development, Flask (Python) for backend services, and MySQL for structured data storage. The integration of Gemma-3 LLM with RAG ensures reduced hallucination, improved explainability, and enhanced diagnostic accuracy. By combining AI-driven reasoning, cloud scalability, and user-friendly interfaces, the system offers a comprehensive and practical approach to modern livestock healthcare.

In summary, this work contributes an intelligent, scalable, and explainable AI-driven framework for livestock disease analysis and veterinary consultation. The proposed system not only improves early disease detection and treatment accuracy but also supports sustainable farming practices by reducing economic losses and enhancing animal welfare. This research demonstrates the effective application of Generative AI and RAG- based architectures in the agricultural domain and lays the foundation for future advancements in smart livestock health management systems.

II. LITERATURE SURVEY

The rapid growth of the global livestock industry has intensified the need for intelligent health monitoring and disease management systems. Livestock diseases not only affect animal welfare but also cause significant economic losses due to reduced productivity, increased mortality, and higher treatment costs. Conventional disease diagnosis methods rely heavily on farmer experience and periodic veterinary inspections, which are often insufficient for early detection. To overcome these challenges, researchers have increasingly explored artificial intelligence–based approaches for automating disease detection and decision support in livestock healthcare.

Early research efforts primarily focused on traditional machine learning models that utilized structured datasets, environmental parameters, and historical disease records to predict livestock diseases [5], [9]. These systems demonstrated that AI could assist in identifying disease patterns; however, they required extensive manual feature engineering and lacked robustness when exposed to real-world variability. Furthermore, such approaches were limited in handling unstructured inputs like images and natural language descriptions provided by farmers.

With advancements in deep learning, image-based disease detection became a prominent research direction. Several studies employed Convolutional Neural Networks (CNNs) to analyze livestock images for identifying visible symptoms such as skin lesions, wounds, and abnormal physical traits [6], [12], [16]. Machine vision techniques further automated feature extraction and improved classification accuracy [13]. Although these image- based approaches achieved notable success, they functioned largely as black-box models and failed to provide reasoning or explanations for their predictions, which limited user trust and practical adoption.

To address transparency concerns, explainable artificial intelligence (XAI) frameworks were introduced in livestock disease detection systems. Vardhan et al. [1] proposed an integrated ML/DL framework that emphasized interpretability and explainable outputs to improve decision-making reliability. Similar trends were observed in healthcare-oriented XAI research [23], where explainability was identified as a critical requirement for deploying AI in safety-critical domains. Despite these advancements, most XAI-based livestock

systems remained constrained to static datasets and lacked real-time adaptability or expert-in-the-loop mechanisms.
Alternative approaches such as fuzzy logic models were explored to manage uncertainty and imprecision in symptom reporting. Mustapoevich [2] demonstrated that fuzzy rule-based systems could effectively process vague symptom descriptions. While these systems are intuitive and interpretable, their performance is highly dependent on expert- defined rules and they lack scalability when extended to diverse disease categories or evolving veterinary knowledge.

Several comprehensive review studies have highlighted the expanding role of AI in agriculture and livestock health management. Kumar et al. [4] and Nawaz et al. [7] surveyed machine learning and deep learning techniques across livestock, fisheries, and crop management, emphasizing the need for intelligent decision-support systems. Poultry- focused reviews [8] further reinforced the applicability of AI-based disease detection across animal species. These surveys consistently identified gaps such as limited multimodal intelligence, lack of real-time advisory systems, and minimal integration with cloud-based platforms.

Recent studies have explored cloud-enabled smart farming solutions to enhance scalability and accessibility. Cloud-based AI systems have enabled real-time data processing, centralized storage, and remote access to disease analytics [22]. Smart livestock monitoring frameworks combining automation and predictive analytics have also been proposed [21]. However, most such systems rely heavily on sensor data and do not incorporate generative reasoning, natural language interaction, or dynamic medical knowledge retrieval.

The emergence of Large Language Models (LLMs) has significantly transformed intelligent decision- support systems by enabling advanced reasoning, contextual understanding, and human-like interaction. Foundational transformer-based studies [17], [19] established the core principles behind modern LLMs, while Vision Transformers expanded deep learning capabilities in image understanding [20]. In medical and healthcare domains, LLMs have demonstrated strong potential for clinical decision support and explanation generation [15]. However, standalone LLMs are prone to hallucinations and may generate unreliable outputs when domain-specific knowledge is required.

To mitigate these limitations, Retrieval-Augmented Generation (RAG) was introduced as a hybrid framework that combines generative models with external knowledge retrieval [18]. Advanced RAG architectures such as MEGA-RAG [11] further enhanced reliability by incorporating multi-evidence guided reasoning. These approaches have proven effective in public health and medical domains and offer valuable insights for veterinary and livestock healthcare applications.

In the livestock domain, Han et al. [10] proposed a RAG-based AI knowledge assistant for goat farmers, demonstrating improved accuracy through domain- specific retrieval. However, the system was primarily text-based and did not integrate image- based disease analysis. Research on multimodal learning [14], [24] highlights that combining visual, textual, and contextual data significantly improves diagnostic accuracy, yet such integrated frameworks remain underexplored in livestock healthcare.

Overall, the reviewed literature reveals that existing systems tend to address isolated components of livestock disease management, such as image classification, rule-based reasoning, or predictive modeling. There is a clear absence of comprehensive systems that integrate multimodal inputs, explainable reasoning, dynamic knowledge retrieval, and real-time veterinary consultation within a unified framework. Moreover, the use of dual-LLM architectures to separately handle symptom extraction and disease reasoning is largely unexplored in current livestock health solutions.

III. METHODOLOGY

A. Data Acquisition and Multimodal Input Collection

The proposed system begins with the acquisition of multimodal livestock health data from farmers through a mobile and web-based application. Farmers upload high-resolution images of affected animals along with detailed textual descriptions of observable symptoms such as abnormal behavior, reduced feed intake, fever, wounds, or skin abnormalities. This combined image–text input enables comprehensive disease understanding by capturing both visual manifestations and contextual clinical information. The system also records metadata such as animal type, age, and duration of symptoms to improve diagnostic accuracy.

B. Image Preprocessing and Visual Feature Extraction

To ensure reliable analysis, uploaded images undergo preprocessing techniques including resizing, contrast enhancement, noise filtering, and normalization. These steps improve image clarity and remove irrelevant distortions. A Convolutional Neural Network (CNN) is then employed to automatically extract discriminative visual features associated with livestock diseases, such as lesions, inflammation, discoloration, or abnormal body posture. Deep feature representations generated by the CNN enable robust pattern recognition even under varying lighting and environmental conditions.

C. Symptom Interpretation Using First Large Language Model (LLM-1)

The first Large Language Model (LLM-1) processes the farmer-provided textual symptom descriptions using natural language understanding techniques. It identifies key clinical indicators, extracts medical entities, determines symptom severity, and interprets temporal patterns. The unstructured text is converted into a structured symptom representation, which includes standardized medical terminology. This step reduces ambiguity and ensures consistent input for downstream reasoning processes.

D. Knowledge Retrieval through Retrieval- Augmented Generation (RAG)

The structured symptom data and extracted image features are passed to a Retrieval-Augmented Generation (RAG) framework. Relevant veterinary knowledge is retrieved from a vector database hosted on a cloud platform. This database contains disease profiles, vaccination schedules, treatment protocols, preventive guidelines, and peer-reviewed veterinary literature. The retrieval mechanism ensures that onlycontextually relevant and evidence-based information is used, significantly reducing hallucinations commonly observed in standalone language models.

E. Disease Reasoning and Diagnosis Using Second Large Language Model (LLM-2)

The second Large Language Model (LLM-2) performs advanced reasoning by integrating multimodal inputs and retrieved knowledge. It analyzes correlations between symptoms, visual indicators, and disease patterns to predict probable livestock diseases. The model also evaluates confidence levels and generates explainable diagnostic outputs, clearly stating the reasoning behind each prediction. This explainability enhances trust and usability among farmers and veterinary professionals.

F. Recommendation Generation and Veterinary Consultation Module

Based on the diagnosis, the system generates personalized recommendations including immediate care instructions, preventive measures, vaccination alerts, and treatment suggestions. Severity assessment is used to determine whether expert intervention is required. In critical cases, the system automatically initiates a veterinarian consultation, enabling direct communication between farmers and professionals. This human-in-the-loop approach ensures clinical validation and reduces the risk of incorrect decision-making.

G. Cloud Deployment, Monitoring, and User Interface Integration

The entire system is deployed on a cloud platform to ensure scalability, high availability, and secure data management. A user-friendly web and mobile interface enables farmers to upload images, enter symptoms, receive diagnostic results, and access veterinary guidance in real time. Cloud-based logging and monitoring further support continuous system improvement, fault detection, and performance optimization under varying user loads. Role-based access control is implemented to protect sensitive data and ensure secure interaction between farmers, veterinarians, and system administrators.

RESULTS AND DISCUSSION

The proposed Gen AI–driven Livestock Disease Analysis and Vet Consultation Assistant demonstrated effective performance in early disease identification and decision support by integrating image-based analysis, symptom understanding, and knowledge-driven reasoning. The CNN-based image processing module accurately extracted visual disease features, while the dual-LLM architecture enhanced diagnostic precision by combining textual symptom interpretation with retrieved veterinary knowledge through the RAG framework. This multimodal fusion significantly reduced misclassification compared to traditional single- modal systems. The system generated explainable diagnostic outputs, including probable disease identification, preventive measures, and treatment recommendations, improving transparency and user trust. Automatic veterinarian consultation was successfully triggered in critical or uncertain cases, ensuring expert validation. Cloud deployment enabled real-time processing, scalability, and seamless accessibility across mobile and web platforms. Although system accuracy depends on image quality, data availability, and network connectivity, the overall results confirm that the proposed approach improves diagnostic reliability, supports timely intervention, and effectively bridges the communication gap between farmers and veterinary professionals, leading to enhanced livestock health management and reduced economic losses.

IV. CONCLUSION

This project successfully presents a Gen AI–driven Livestock Disease Analysis and Vet Consultation Assistant that integrates multimodal data processing, dual Large Language Models, and Retrieval- Augmented Generation to enable accurate, explainable, and timely disease diagnosis. By combining image-based feature extraction with symptom-level contextual understanding, the system overcomes the limitations of traditional rule-based and single-model diagnostic approaches. The incorporation of a cloud-hosted veterinary knowledge base ensures reliable, evidence-backed predictions while minimizing hallucinations. Automated recommendation generation and intelligent veterinarian consultation further strengthen decision support and early intervention capabilities. The cloud-based web and mobile deployment enhances scalability, accessibility, and real-time usability for farmers. Overall, the proposed system bridges the gap between farmers and veterinary professionals, supports proactive livestock health management, reduces economic losses, and demonstrates the practical applicability of Generative AI in smart agriculture and digital veterinary care.

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