



Artificial Intelligence in Smart Dairy Farming: A Review of Cattle Breed Recognition, Milk Production Prediction, and Voice-Based Assistance

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ABSTRACT

Artificial intelligence (AI) is being investigated in dairy farming for image-based animal analysis, milk-production forecasting, and access to agricultural information. These tasks use different data and methods: cattle recognition commonly uses computer vision and deep learning, milk-yield prediction uses historical records and machine-learning models, and conversational assistants use information retrieval and natural-language processing. This review examines representative research in these areas and considers multilingual speech technologies as a potential interface for farmers who prefer speaking rather than typing. Published studies show promising applications, but reported results depend on datasets, evaluation conditions, and the task being measured. The review identifies challenges involving dataset diversity, record quality, evidence-grounded answers, regional-language speech recognition, and real-world validation. Based on these findings, it discusses the proposed CowCare AI concept, which brings breed recognition, milk-production prediction, and a dairy question-answering assistant together in one farmer-oriented application. The paper presents an initial targeted review rather than an exhaustive systematic review; its conclusions should therefore be interpreted as a synthesis of selected literature.

Keywords: Artificial intelligence, smart dairy farming, cattle breed recognition, milk production prediction, machine learning, retrieval-augmented generation, multilingual voice assistant, precision agriculture.

Introduction

Dairy farming involves decisions about animal identification, milk production, feeding, health, and day-to-day farm management. Artificial intelligence (AI) and machine learning (ML) are increasingly investigated as tools for analyzing farm data and supporting such decisions. A systematic review examined 427 papers and analyzed 38 primary studies in detail, finding that dairy ML research included disease detection, milk-yield prediction, and milk-quality prediction [1]. A later scoping review of AI and data analytics in dairy farms identified 151 relevant articles and reported that milk prediction and animal-health monitoring were prominent topics [2].

Cattle breed recognition is one potential application of computer vision. Deep-learning models can learn visual features from images and classify animals, but performance depends on image quality, dataset coverage, and the similarity between breeds. Milk-production prediction is a different task: it uses historical production records and other variables to estimate future yield. Conversational systems provide a third capability by allowing users to ask questions about documents or structured records in natural language [1], [3].

Voice interaction may make agricultural information systems easier to use for farmers who prefer speaking to typing or reading long text. For a multilingual system, speech recognition and speech synthesis must work well with the selected languages and realistic recording conditions. Research on speech recognition for Indian languages in an agricultural commodities domain provides relevant background for this challenge [4].

This paper reviews selected literature on cattle recognition, milk-production prediction, agricultural question-answering, and Indian-language speech technologies. It compares their methods and limitations, identifies integration challenges, and discusses how these technologies could inform CowCare AI. The aim is not to claim that the proposed application has already demonstrated improved farm outcomes, but to identify a research-informed design and the testing it would require.

Review Methodology

This paper uses a targeted literature-review approach. Sources were identified through searches of academic publisher pages and scholarly search results, including ScienceDirect, Springer Nature, MDPI, PubMed Central, and institutional journal websites. Search concepts included cattle breed recognition

using deep learning, machine learning for milk-yield prediction, dairy-farm management, agricultural question-answering, and speech recognition in Indian languages. The search was exploratory rather than exhaustive, and the search dates, exact result counts, and duplicate-removal counts were not systematically recorded.

Studies were considered relevant when they addressed at least one of the review's four areas: (1) cattle recognition or computer vision, (2) milk-production prediction, (3) agricultural or dairy question-answering, or (4) multilingual speech interaction. Priority was given to original research articles and review papers with identifiable publication details and a described method or scope. Sources from adjacent agricultural domains were included only when their methods were relevant to the proposed assistant.

The selected studies were compared by research objective, method, data type, reported findings, and limitations. Numerical results are retained only when reported by the source and are interpreted in their original context. Results from different datasets and tasks are not treated as directly comparable. This is a targeted narrative review, not an exhaustive systematic review; its selection process is therefore not intended to support a claim of complete coverage.

Cattle Breed Recognition

Computer vision can support livestock identification by analyzing visual information in photographs. Convolutional neural networks (CNNs) learn image features through successive convolution and pooling operations. A classifier then maps those features to a predicted category. In a practical setting, performance can be affected by pose, lighting, background clutter, occlusion, and the presence of breeds that were not represented during training.

A lightweight deep-learning approach for identifying and classifying indigenous cattle breeds, focusing on Tharparkar and Hariana cattle, has been reported [5]. The reported classification accuracy was 72.5%, illustrating that distinguishing visually similar breeds can remain difficult. The result should be interpreted in relation to the study's dataset and experimental setup rather than treated as a general accuracy level for cattle recognition.

A systematic review of deep-learning applications for precision cattle farming [3] identified studies involving cattle identification and health monitoring and discussed the use of CNNs and related architectures. The broader literature suggests that deep learning can support visual livestock tasks, but datasets and evaluation protocols vary substantially. An important distinction is the difference between breed classification and individual-animal identification. Breed classification predicts a breed category; individual identification attempts to determine which particular animal is shown. A high score on one task does not establish performance on the other. For CowCare AI, the model should state its supported breeds, be tested on images not used for training, and communicate uncertainty when image quality is poor or the predicted breed is outside its supported categories.

Table 1. Comparison of cattle-breed recognition research

Study / source	Task and method	Evidence reported	Limitation
Deep-learning review [3]	Review of deep learning in cattle farming	Screened 678 studies; analysed 56 eligible studies	Broad cattle-identification and health scope; not a single benchmark
Indigenous-breed CNN study [5]	CNN segmentation and breed classifier	72.5% classification accuracy for Tharparkar vs. Hariana	Two visually similar breeds; broader and more diverse validation is needed
CowCare AI (proposed)	Image classifier using EfficientNet-B0	No project accuracy claimed in this review	Requires a documented dataset and testing on held-out animals/images

Milk-Production Prediction

Milk-production prediction typically uses historical yield records and other available variables to estimate future output. Potential inputs include previous daily or monthly yields, lactation stage, milking parameters, cow characteristics, and farm-level variables. The useful inputs depend on the prediction horizon and on what information a farm can reliably collect.

A systematic review of machine-learning approaches for dairy-farm management found that yield and milk-quality prediction were among the research categories, alongside a larger focus on disease detection [1]. The input variables and algorithms used in the studies were grouped, illustrating that dairy prediction is not a single modelling problem: it includes different targets, data sources, and evaluation conditions.

Deep learning has been investigated to predict the milk-yield curve in a subsequent lactation period using previous lactation information [6]. Other research has explored prediction of milk yield from earlier test-day or part-lactation records, including studies on Sahiwal cattle [7]. These approaches are relevant to settings where reliable production history is available.

Milk prediction can be formulated as regression or time-series forecasting. Candidate models include linear regression, random forests, gradient boosting, and neural networks. They should be compared on the same data split and against simple baselines. Useful regression metrics include mean absolute error

(MAE), root mean squared error (RMSE), and the coefficient of determination (R^2). The paper should report the prediction horizon, units, test-set design, and data source alongside any metric. For CowCare AI, milk prediction should be treated as an estimate rather than a guarantee. A model trained on one farm or breed may not generalize to another. Missing records, changes in feed or health, and differences in measurement practices can also affect predictions. A realistic deployment plan should begin with data availability and quality, followed by independent validation.

Table 2. Comparison of milk-production prediction research

Study / source	Prediction target	Method / evidence	Key implication
Lactation-curve study [6]	Milk-yield curve in subsequent lactation	Deep learning using previous lactation information	Temporal history can inform forecasts; external validation remains important
Sahiwal part-lactation study [7]	305-day milk yield in Sahiwal cattle	AI using monthly part-lactation records	Breed- and record-specific modelling should be considered
Dairy analytics scoping review [2]	Scoping review of dairy-farm analytics	151 articles included in review	Historical data are commonly used; review reports do not establish CowCare performance
CowCare AI (proposed)	Farm-level milk-yield estimate	Planned XGBoost regression	Report MAE/RMSE/ R^2 on held-out records; do not claim accuracy before testing

Dairy Question-Answering and RAG

Farmers may need to consult manuals, extension resources, farm records, and scientific documents. Natural-language question-answering can reduce the effort required to find relevant information. However, asking questions about numerical records is different from asking questions about a document collection: the former may require structured database queries, while the latter may require document retrieval.

Dairy GPT enables dairy farmers to interact with numerical databases through natural-language questions [8]. The work compares approaches including prompting, retrieval-augmented generation (RAG), and natural-language-to-SQL (NL2SQL). It is relevant because it treats access to dairy records as a conversational interaction. AgAsk is an agent designed to answer farmers' questions using scientific documents [9]. The study is relevant to document retrieval and agricultural question-answering, although a system developed around one agricultural document collection cannot automatically be assumed to work equally well for dairy-care information.

In a typical RAG pipeline, the system retrieves passages related to a user's question and provides them as context to a language model. This can make an answer more closely grounded in a selected collection, but it does not guarantee correctness. Poor source documents, failed retrieval, ambiguous questions, or unsupported model-generated statements can still lead to incorrect answers. A responsible dairy assistant should cite or identify its information sources where possible, distinguish general information from farm-specific records, and say when it cannot answer reliably.

For CowCare AI, document-based RAG could be used for selected dairy-management resources, while structured queries could handle questions about recorded milk yields. The two functions should be evaluated separately and together. Animal-health questions require particular care: the assistant should not present generated text as a veterinary diagnosis and should direct urgent or serious cases to a qualified veterinarian.

Table 3. Agricultural conversational systems and design implications

Study / source	User task	Approach / evidence	Lesson for CowCare AI
AgAsk study [9]	Answering growers' questions	AgAsk uses neural passage ranking and supports text/voice interaction	Retrieval quality and concise answers matter
Dairy GPT study [8]	Natural-language access to dairy numerical records	Dairy GPT studies conversational access to dairy data; findings are limited to its reported test setup	Structured-data questions may require NL2SQL; validate against representative questions
CowCare AI (proposed)	Dairy knowledge Q&A	RAG using curated resources, embeddings, FAISS, and an LLM	Needs source-grounded answers, retrieval tests, and a safe fallback when evidence is missing

Multilingual Voice Interaction

Voice-based interaction can provide an alternative to typing, especially for users who are more comfortable speaking in their preferred language. A typical system includes automatic speech recognition (ASR), question processing, answer generation, and text-to-speech (TTS). A multilingual application must also manage language selection and the possibility that a user changes language or mixes terms within a sentence.

Acoustic modelling for speech recognition in Indian languages has been studied in an agricultural commodities task domain, including Hindi and Marathi [4]. That work highlights the importance of acoustic modelling and differences that may arise between speech corpora and recording conditions. AgAsk also demonstrates a conversational agricultural search interface that accepts text or voice questions and returns short natural-language answers [9]. These studies provide relevant context, although neither establishes the performance of a multilingual dairy-care assistant.

Practical voice use introduces several challenges. Background noise from animals, machinery, wind, or nearby conversation can reduce transcription accuracy. Regional accents, pronunciation variation, and dairy-specific vocabulary may also cause errors. Furthermore, a correct transcription does not ensure that the answer produced by the assistant is correct; the question-answering component must be evaluated separately.

A proposed CowCare AI voice pipeline is: (1) the farmer selects Marathi, Hindi, or English or the system detects the language; (2) ASR converts speech to text; (3) the dairy assistant retrieves information or queries records; (4) the answer is generated in the selected language; and (5) TTS reads the answer aloud. This is a proposed architecture, not a feature whose performance has already been validated. Evaluation should include speech-recognition error rates, answer relevance and factual correctness, response time, language-specific performance, and usability with representative users. The system should allow users to correct a misheard question and should provide a text alternative when speech recognition or speech synthesis is unavailable.

Comparative Analysis

The reviewed work addresses complementary parts of a potential dairy-support application. Computer-vision research focuses on extracting information from images; milk-prediction research estimates future yield from historical records; question-answering systems connect user questions with documents or databases; and speech systems provide an alternative input and output channel. Each component requires a different evaluation method.

Table 4. Comparative summary of CowCare AI research areas

Research area	Common method	Potential strength	Key limitation
Breed recognition	CNNs / deep learning	Visual classification from images	Dataset diversity and visually similar breeds
Milk prediction	Regression / ML / time-series	Uses historical production records	Requires reliable records and validation
Dairy Q&A	RAG, NLP, database queries	Natural-language access to information	Retrieval quality and answer correctness
Voice interface	ASR and TTS	Hands-free regional-language interaction	Noise, accents, and language coverage

Research Gaps and Future Directions

First, integration remains an engineering and evaluation challenge. Separate demonstrations of image classification, yield prediction, and question-answering do not establish that a combined application will be useful or reliable. An integrated system needs clearly defined data interfaces and separate module-level testing as well as end-to-end evaluation.

Second, model generalization needs attention. Cattle images should cover the breeds and field conditions expected in deployment. Milk-prediction models require representative records and validation on unseen data. The system should avoid presenting predictions with unjustified certainty.

Third, agricultural question-answering requires trustworthy source material and a method for handling missing evidence. A curated dairy knowledge collection, retrieval evaluation, source attribution, and fallback responses can reduce, but not eliminate, the risk of unsupported answers.

Fourth, multilingual voice support should be evaluated in Marathi, Hindi, and English using realistic vocabulary, accents, and background noise. Language support should be confirmed through testing rather than inferred from a library or service's general capabilities.

Finally, future studies should involve representative farmers and dairy practitioners. Evaluation can measure task completion, perceived ease of use, answer correctness, response time, and the rate at which users need to repeat or correct their questions. Veterinary safety guidance should be reviewed by qualified professionals.

Table 5. Research gaps and evaluation priorities for integrated dairy AI

Research gap	Why it matters	Recommended evaluation
Dataset representativeness	Breed, age, lighting, camera angle, and farm differences can affect image predictions	Held-out animals; per-class precision, recall, F1, and confusion matrix
Milk-model generalization	Milk records vary by breed, lactation stage, feeding, and management	Time-aware test split; MAE, RMSE, R^2 ; compare with a simple baseline
Grounded question-answering	Language models may produce plausible but unsupported answers	Retrieval recall, answer correctness, source support, and abstention rate
Multilingual speech	Noise, accents, and dairy vocabulary can cause transcription errors	Word error rate (WER) by language, latency, task completion, and user feedback
Integrated-system usability	Individual model results do not prove usefulness of the complete app	Scenario-based tests with representative users and documented limitations

Conclusion

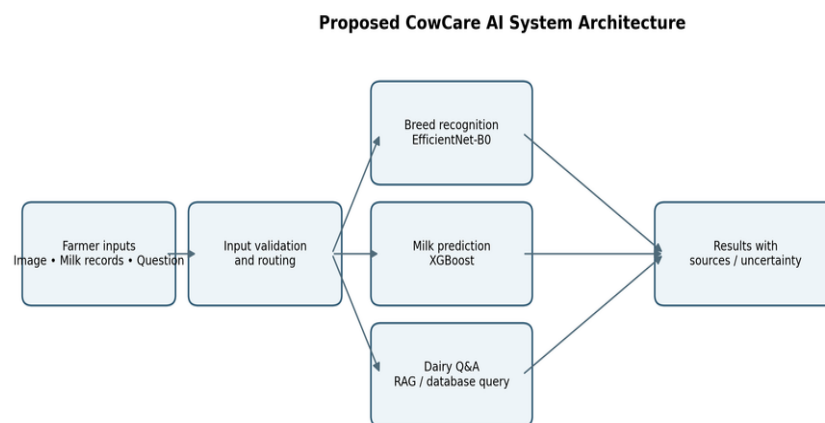
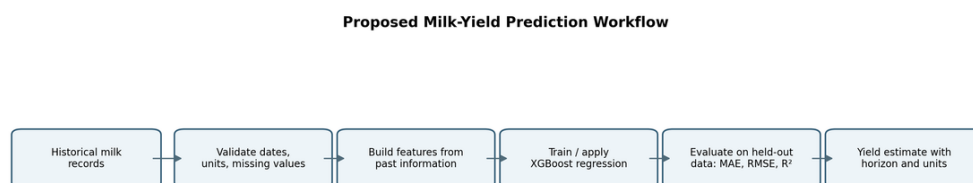
Artificial intelligence offers several ways to support dairy farming, including cattle image analysis, milk-production forecasting, and conversational access to agricultural information. The literature reviewed in this paper shows that these areas have been investigated using different methods and datasets. Research on Indian-language speech recognition also provides a foundation for considering voice-based access in agricultural settings.

Each capability has limitations: visual recognition depends on image diversity, milk prediction depends on data quality and validation, question-answering depends on retrieval and source reliability, and voice interaction depends on speech conditions and language coverage. These limitations mean that a combined system should be evaluated carefully rather than assumed to be reliable because its individual technologies exist.

CowCare AI is proposed as an integrated application combining cattle breed recognition, milk-production prediction, and a dairy assistant with multilingual voice interaction. Its potential contribution is to make these functions accessible through one farmer-oriented interface. Implementation, representative testing, source verification, and feedback from intended users are required before claims about practical effectiveness can be made.

This paper does not report an experimental evaluation of the complete CowCare AI application. The architecture and module choices described here are proposed design elements; their accuracy, usability, and field performance must be established through future testing.

Proposed CowCare AI Flowcharts

**Figure 1. Proposed CowCare AI system architecture (conceptual; not experimentally validated).****Figure 2. Proposed milk-yield prediction workflow.**

Proposed Multilingual Voice Assistant Workflow**Figure 3. Proposed multilingual voice assistant workflow.****Acknowledgements**

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