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GauDrishti: An AI- and IoT-Enabled Early-Risk Decision-Support System for Bovine Mastitis in Indian Dairy Farms : *A Multi-Sensor Collar Prototype with Three Independent AI Signals*

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Abstract

Bovine mastitis is a major challenge for dairy farmers because early signs are difficult to notice and timely intervention is often limited. This paper presents GauDrishti, an AI- and IoT-enabled decision-support system that combines real-time sensor data, historical records, milk information and manual or laboratory inputs for continuous animal monitoring. A low-cost collar built around an ESP8266 node carries an MPU6050 motion sensor, a DS18B20 temperature sensor, an SHT31-D ambient temperature and humidity sensor, a MAX9814 microphone and a status LED. Data reach a FastAPI and MongoDB back end over MQTT or HTTPS, where 72 engineered longitudinal features are computed. Three independent AI signals are produced: Temporal AI (XGBoost with SHAP explanations, giving development-stage 7-day and 14-day forecasts), a Behaviour Signal based on deviation of activity and rumination from an animal-specific baseline, and Udder Vision (Ultralytics YOLO11). These are combined into an AI Health View that supports animal-level and herd-level prioritisation, early warning alerts and actionable recommendations for farmers and veterinarians, with a human in the loop. The hardware prototype costs approximately ₹1.5K–₹2K. Because labelled clinical onset timelines were

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limited, development used public and synthetic data; no clinical validation or predictive performance is reported here, and prospective validation against veterinary review and CMT/SCC is planned.

Keywords : bovine mastitis, AIoT, early warning, decision support, longitudinal modelling, XGBoost, SHAP, YOLO11, precision dairy farming

I. Introduction

Mastitis is a major health and productivity problem for dairy farmers. Its early signs are difficult to notice, and in many settings it is recognised only after visible clinical signs appear. Continuous observation of every animal is difficult on farms, and the information that would help, such as sensor readings, animal records, milk data and farm observations, is usually scattered across separate sources. Manual screening therefore makes it hard to decide which animals need attention first.

Prior research has explored sensor-based machine learning, IoT data fusion, multivariable time-series models and forecasting from Automatic Milking System (AMS) data for mastitis prediction (Section II) [1]–[5]. Small and diverse dairy farms, however, need an approach that is affordable, practical and aligned with the way farmers and veterinarians already work. Such an approach should also state clearly what its outputs can and cannot mean, since a risk cue is not a diagnosis.

This paper presents GauDrishti, an AI- and IoT-enabled decision-support system for early-risk monitoring of bovine mastitis. It combines (i) a low-cost multi-sensor collar, (ii) a data pipeline that validates and synchronises real-time and historical data, (iii) three independent AI signals, and (iv) an AI Health View that prioritises animals for review. The contributions are: (1) an integrated architecture from on-animal sensing to farmer and veterinarian decision support; (2) three independent AI signals (Temporal AI, Behaviour Signal and Udder Vision) that remain individually reviewable before they are combined; (3) a low-cost, modular collar design and software stack intended for practical dairy deployment; and (4) an explicit risk-and-response framework and staged validation path that state which parts are implemented, which are under development and which require clinical validation.

Section II reviews related work, Section III describes the architecture, Section IV the hardware, Section V the data pipeline, software and dashboard, and Section VI the analytics. Section VII presents deployment evidence and the validation methodology, Section VIII the feasibility and impact analysis, and Sections IX and X give limitations and conclusions.

II. Related Work

Table I lists the five research papers that inform GauDrishti, together with the relevance of each as stated in the project documentation. Zhou et al. [1] support sensor-based machine learning for mastitis prediction from multi-source data. Anwar et al. [2] support the integration of IoT sensors and data fusion for early detection. Fan et al. [3] inform the use of multivariable time-series models for early prediction. Li et al. [4] support forecasting approaches that use AMS sensor data, and Ebrahimi et al. [5] provide baseline machine-learning approaches for sub-clinical mastitis prediction.

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TABLE I

RESEARCH PAPERS INFORMING GAUDRISHTI

Ref.	DOI	Relevance to GauDrishti (from the project documentation)
[1] Zhou et al. (2024)	10.3390/ani14030427	Sensor-based machine learning for mastitis prediction using multi-source data
[2] Anwar et al. (2025)	10.1145/3709982.3790013	Integration of IoT sensors and data fusion for early detection
[3] Fan et al. (2023)	10.3168/jds.2023-23356	Multivariable time-series models for early prediction of mastitis
[4] Li et al. (2025)	10.1016/j.compag.2022.107002	Forecasting approaches using Automatic Milking System sensor data
[5] Ebrahimi et al. (2019)	10.1016/j.compbiomed.2019.103456	Baseline ML modelling approaches for sub-clinical mastitis prediction
This work	—	**Collar-based multi-source sensing, longitudinal features, three independent AI signals, animal- and herd-level prioritisation**

The project also compares its approach with the current farm workflow (Table II). Existing practice relies on periodic observation, reactive follow-up, disconnected data sources and manual herd screening, which leave gaps in trend visibility, early prioritisation, context and review burden. GauDrishti addresses each gap with longitudinal monitoring, a risk-oriented attention cue, an integrated multi-source pipeline and combined animal-level and herd-level prioritisation. The papers above are used as methodological support; the paper does not claim performance beyond what its own validation will establish.

TABLE II

CURRENT WORKFLOW COMPARED WITH GAUDRISHTI

Current workflow	Gap	GauDrishti
Periodic observation	Limited trend visibility	Longitudinal monitoring
Reactive follow-up	Limited early prioritisation	Risk-oriented attention cue
Disconnected data sources	Context fragmentation	Integrated multi-source pipeline
Manual herd screening	Higher review burden	Animal + herd prioritisation

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III. System Architecture

The system follows a six-step methodology: **Sense → Ingest → Context → Three independent AI signals → Prioritise → Act**. In the sensing step, IoT sensors on the collar, farm records and manual or laboratory inputs supply data. In the ingest step, real-time and historical multi-source data are received. In the context step, data are validated and synchronised and longitudinal features are built. Three independent AI signals are then computed, an AI Health View supports animal-level and herd-level prioritisation, and early warnings lead to prioritised review and a recommendation.

The architecture in Fig. 1 has five blocks. Block 01, the **GauDrishti Collar**, is an ESP8266-based edge node that acquires sensor data, performs local processing and buffering, and communicates wirelessly. Block 02, **data ingestion and validation**, uses MQTT, HTTPS and a FastAPI REST interface. Block 03, the **longitudinal data engine**, stores historical and time-series animal context in MongoDB and computes 72 engineered features. Block 04 produces the **three independent AI signals**. Block 05, the **AI Health View and decision support**, presents animal-level and herd-level assessments to the farmer or veterinarian. A feedback loop returns new observations (farmer and veterinarian feedback, laboratory results and treatment outcomes) to the longitudinal health context.

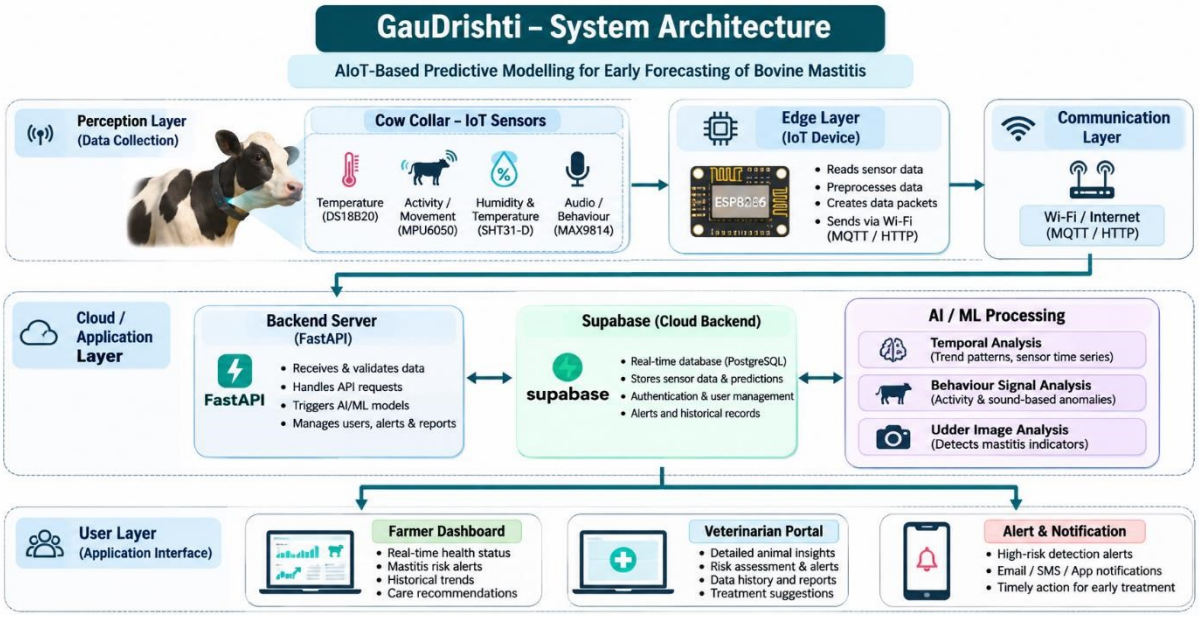


Fig. 1. System architecture of GauDrishti (source: project presentation, slide 3; the "Demo Video" link overlay is part of the original slide).

Fig. 2 shows the operational flow. Data from sensors, animal records, milk data and manual or laboratory inputs are collected and turned into a health context. The three AI signals are then evaluated against an attention threshold. If the threshold is not reached, monitoring continues. If it is reached, an AI Health View with risk factors, a risk score and animal context is generated, and the farmer or veterinarian receives an early warning with a suggested action. Follow-up, treatment and outcomes update the health context.

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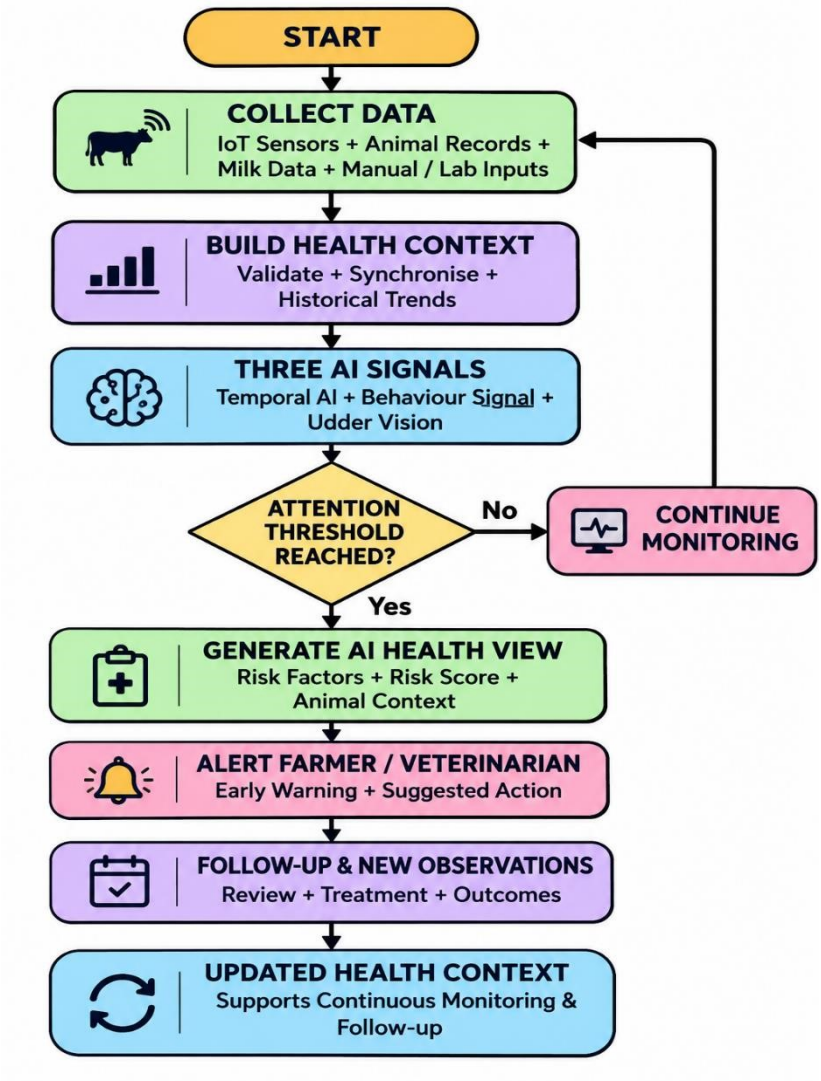


Fig. 2. System flowchart of GauDrishti (source: project presentation, slide 2).

Throughout this paper, the system is positioned as decision support. Technology supports the workflow and does not replace the human decision: veterinary review takes place before action, and the final interpretation rests with the veterinarian.

IV. Hardware Design

A. Controller and Local Functions

The collar is built on an ESP8266 (ESP-12E / NodeMCU) module. As presented, the edge node performs data acquisition, local processing and data buffering, and connects wirelessly Buffering allows the node to hold readings and synchronise them when rural connectivity returns. Firmware is written in Embedded C.

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B. Sensors and Their Roles

Four sensors are mounted on the animal (Table III). The MPU6050 provides activity and movement information over I²C. The DS18B20 measures body or surface temperature on a 1-Wire bus. The SHT31-D reports ambient temperature and humidity over I²C, and this environmental context is the likely basis for the temperature-humidity index (THI) used as a longitudinal feature. The MAX9814 microphone, read through an analog input, provides audio for behaviour monitoring. Together they supply activity, rumination, temperature and environmental information for continuous monitoring.

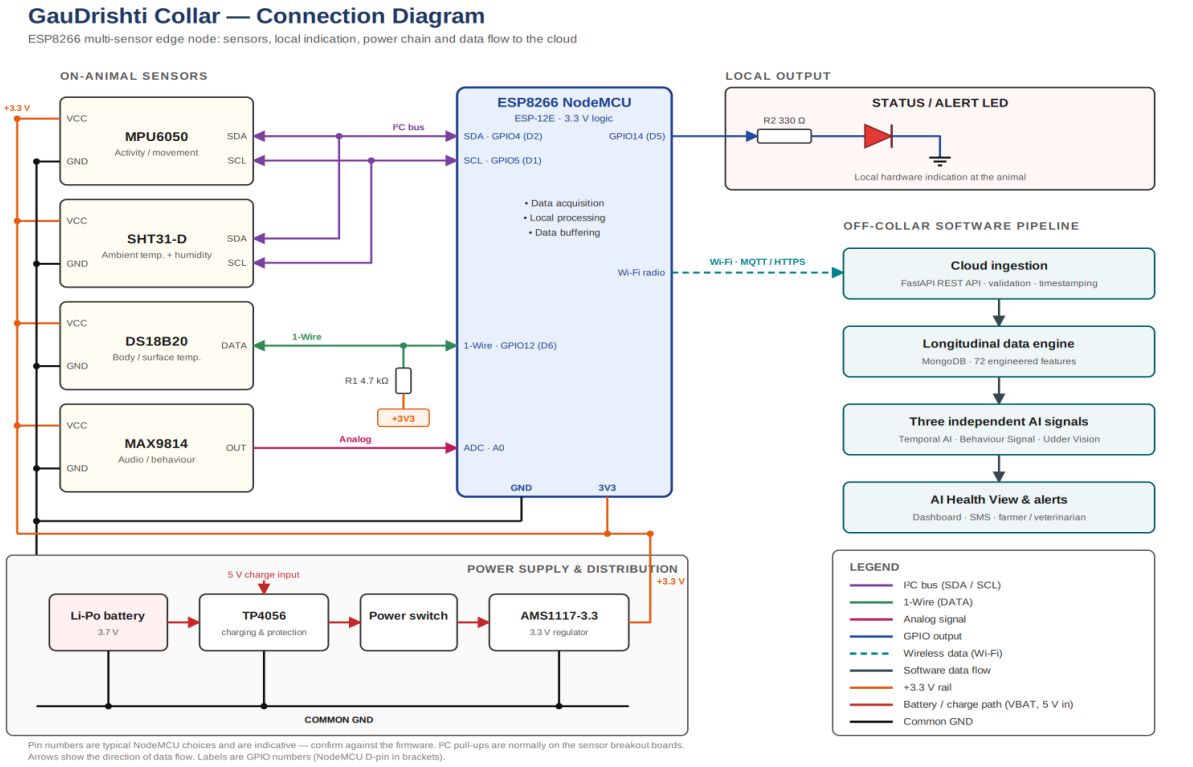
TABLE III

ON-ANIMAL SENSORS OF THE GAUDRISHTI COLLAR

Sensor	Parameter	Interface	Role in the system
MPU6050	Activity / movement	I²C	Activity input to the Behaviour Signal and to longitudinal features
DS18B20	Body / surface temperature	1-Wire	Temperature indicator for animal health context
SHT31-D	Ambient temperature and humidity	I²C	Environmental context; THI feature
MAX9814	Audio / behaviour	Analog	Behavioural indicators

Sensor variability and field placement are recognised risks. The project addresses them through calibration, an animal-specific baseline and validation checks (Section VII).

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C. Local Indication and Power

A status and alert LED, driven from a GPIO pin through a 330 Ω resistor, gives a local hardware indication of the animal's status to a farmer who does not use the dashboard. The power system consists of a 3.7 V Li-Po battery, a TP4056 charging and protection module, a power switch and an AMS1117-3.3 regulator, which supplies 3.3 V (VCC) to the electronics.

D. Prototype and Cost

A working collar prototype has been built, and its enclosure is shown in Fig. 3(a). The hardware-only prototype cost is approximately ₹1.5K–₹2K, achieved with commodity components and replaceable sensors. The software layer scales independently of the hardware, and deployment is planned in phases.

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Fig. 3. (a) GauDrishti collar prototype; (b) field implementation on a dairy farm in Pune, Maharashtra.

V. Data Ingestion, Software and Dashboard

A. Data Ingestion and Validation

Collar data are sent to the back end over MQTT or HTTPS, and a FastAPI REST interface receives them. The ingestion layer performs data validation, timestamping, synchronisation, buffering and data-quality checks. Buffered storage and synchronisation when connectivity returns are the planned response to rural network interruptions. The system is described as HTTP- and MQTT-ready.

B. Longitudinal Data Engine

MongoDB stores historical and time-series data together with animal context. Besides the sensor stream, the health context includes animal records, milk information and manual or laboratory inputs, such as somatic cell count (SCC) when available. Where milk parameters are not measured automatically, a manual or laboratory input pathway is used instead of assuming automated testing. From these data the engine computes 72 engineered features, built on rolling 3-day and 7-day windows, trend and delta features, an animal-specific baseline, days in milk (DIM) or lactation phase, THI and behavioural indicators.

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C. Application Layer and Technology Stack

Results are presented through a React and TypeScript web dashboard, SMS alerts and the LED on the collar. The dashboard offers an individual-animal view and a herd-level view, and multilingual and mobile-ready deployment groundwork is in place, since farmers in different regions need an easy-to-use interface. Table IV summarises the stack.

TABLE IV

TECHNOLOGY STACK BY LAYER

Layer	Technologies
Hardware / IoT	ESP8266, MPU6050, DS18B20, SHT31-D, MAX9814; Embedded C
Communication	MQTT; HTTPS / HTTP
AI / model development	Python, PyTorch, scikit-learn, pandas, XGBoost, SHAP, Ultralytics YOLO11
Back end / deployment	FastAPI, REST API, MongoDB, Docker
Front end	React, TypeScript

VI. Analytics: Three Independent AI Signals

The analytics layer is organised around three independent signals. Each can be reviewed on its own before being combined into the AI Health View, so that a reviewer can see which evidence contributes to an alert. The source presentation reports no accuracy, precision, recall or other performance metrics, and none are claimed here.

A. Temporal AI (Health Trends)

Temporal AI uses XGBoost on the longitudinal features to identify changing health patterns. It provides 7-day and 14-day forecasts, both labelled as development-stage, together with longitudinal trend information. SHAP analysis is used to show which features contributed to a prediction, so that the key risk factors can be presented to the user.

B. Behaviour Signal (Activity and Rumination)

The Behaviour Signal is implemented in Python. It compares activity and rumination with an animal-specific baseline and flags deviations or anomalies. It is defined as an attention signal, not a mastitis probability.

C. Udder Vision (Image-Based Analysis)

Udder Vision uses Ultralytics YOLO11. For cows it performs classification, and for buffaloes it performs udder-region segmentation. It is defined as a visual attention signal and is not a validated mastitis classifier.

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TABLE V

THE THREE INDEPENDENT AI SIGNALS

Signal	Method	Output	Stated status
Temporal AI	XGBoost; SHAP	7-day and 14-day forecasts; trends; feature contributions	Development-stage forecasting
Behaviour Signal	Python; animal-specific baseline	Deviation / anomaly in activity and rumination	Attention signal, not a mastitis probability
Udder Vision	Ultralytics YOLO11	Cow: classification; buffalo: udder-region segmentation	Visual attention signal, not a validated classifier

D. AI Health View and Prioritisation

The AI Health View combines signal status, risk factors and an attention threshold to assess each animal, and aggregates these assessments to the herd level. It produces early warning alerts, a prioritised review list and actionable recommendations for the farmer or veterinarian. Follow-up observations, including review, treatment outcomes and laboratory results, return to the longitudinal context so that later assessments include what was learned.

E. Data Used for Development

Multiple public datasets were integrated, covering animal profiles, milk yield and quality, SCC, pH, conductivity, milk and body temperature, activity, rumination and behavioural signals, environmental temperature, humidity, THI and clinical mastitis references. They supported longitudinal feature engineering, calibration and development of the three AI pathways. Where labelled clinical onset timelines were unavailable, synthetic development data were used to build sufficiently long longitudinal sequences for the development-stage 7-day and 14-day forecasts. Public and synthetic datasets support research and development, but they do not replace real-world field validation.

VII. Deployment Evidence and Validation Methodology

A. Field Implementation and Expert Observation

The GauDrishti prototype was implemented and tested under veterinary-domain observation, and expert feedback on the proposed workflow and field applicability was obtained from Dr. Vitthal Chamare, Retired Assistant Livestock Development Officer, Pune District. Fig. 3(b) shows a field implementation in Pune, Maharashtra. A five-farm field dataset is referenced in the project materials.

B. Risks and Engineering Responses

Table VI lists the principal risks identified by the team and the planned engineering response to each.

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TABLE VI

CHALLENGES AND ENGINEERING RESPONSES

Challenge / risk	Engineering response
Sensor variability and field placement	Calibration, animal-specific baseline and validation checks
Rural connectivity	Buffered storage and synchronisation when connectivity returns
Missing milk parameters	Manual / laboratory input pathway instead of assuming automated testing
Farmer adoption	Simple workflow, farmer and veterinary review, multilingual groundwork
Deployment cost at scale	Commodity components, modular replaceable sensors, phased rollout
Limited clinical longitudinal labels	Prospective multi-day collection, veterinary review and CMT/SCC comparison

C. Implementation and Validation Path

Development follows five stages: a working prototype (core system implemented); a field pilot (real-farm testing); prospective clinical validation (multi-day field validation with veterinary review and CMT/SCC comparison); integration with dairy cooperatives; and multi-farm scale deployment. Only the first stage is reported as complete in the source presentation, and the pilot has not yet been reported as producing quantified results.

VIII. Feasibility, Market and Impact

A. Feasibility

The system is **technically** implementable with commodity hardware and open-source software, following the chain Sensors → API → AI/ML → Health View. It is **financially** viable at the prototype scale, with an approximate hardware-only cost of ₹1.5K–₹2K, replaceable sensors and phased deployment. It is **operationally** aligned with farm practice because it uses real-time and historical farm data, farmer inputs, laboratory records where available and veterinary review before action, and it presents information as a dashboard, SMS and an LED.

The market analysis (Table VII) is based on official statistics [6], [7]. The serviceable market is limited to bovines registered in INAPH, and the initial obtainable target of 1 lakh is an illustrative team planning target and not a revenue projection. Target users range from smallholder farmers, through dairy cooperatives and veterinarians, to organised and commercial dairies.

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TABLE VII

MARKET SIZING

Level	Figure	Definition / source
TAM	10.64 crore+	Indian in-milk bovines (DAHD Annual Report 2025–26) [6]
SAM	3.45 crore+	INAPH-registered bovines (DAHD Annual Report 2025–26) [6]
SOM	1 lakh*	Initial deployment target; illustrative team planning target, not a revenue projection

B. Impact and Benefits

For the **farmer**, the system indicates which animal to look at first, so that observation and follow-up can be prioritised. For the **veterinarian**, it supports priority clinical review with animal history, behaviour and vision signals as supporting evidence; final interpretation remains the veterinarian's responsibility. For the **animal**, earlier attention can support improved welfare. For the **dairy ecosystem**, structured animal-health records support monitoring at the individual, herd and farm levels and are useful to cooperatives.

The benefits are economic, animal-health-related, social and environmental. The project cites an estimated annual economic loss from mastitis in India of ₹7,000–₹11,500 crore; the team states that GauDrishti addresses the information gap and that its economic impact requires field validation. Earlier veterinary review, structured follow-up and responsible antimicrobial use support animal health and safer milk. Socially, the approach supports smallholder and marginal farmers, women and rural livelihoods, and farmer–veterinarian coordination. Environmentally, better health records can support preventive herd management, and reduced avoidable treatment and milk-disposal pathways are a potential downstream benefit. The expected impact chain runs from early prediction to early intervention, reduced disease severity, lower treatment and production loss, better milk quality, improved farmer profitability and, finally, improved animal welfare. These are expected effects and are not yet measured.

IX. Limitations

The Temporal AI forecasts are development-stage: labelled clinical onset timelines were unavailable, so synthetic longitudinal sequences and public datasets were used, and these do not replace field validation. The Behaviour Signal is an attention signal and not a mastitis probability, and Udder Vision is a visual attention signal and not a validated mastitis classifier. No predictive performance metrics are reported in this paper. Sensor readings can vary with placement on the animal, and the system depends on calibration and animal-specific baselines. Rural connectivity may be intermittent, so the design relies on buffering and later synchronisation. Milk parameters such as SCC are used when available and are entered manually or from laboratory records, not measured automatically. The economic impact is an estimate that requires field validation, and the serviceable-market target is an illustrative planning figure. Finally, the system provides decision support only: veterinary review is needed before any action.

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X. Conclusion and Future Work

This paper presented GauDrishti, an AI- and IoT-enabled early-risk decision-support system for bovine mastitis. It combines a low-cost multi-sensor collar, a validated and synchronised longitudinal data pipeline and three independent AI signals into an AI Health View that supports animal-level and herd-level prioritisation, early warning alerts and actionable review by farmers and veterinarians. It documented the sensing hardware, the software stack, the risks and their planned responses, and the staged path from a working prototype to multi-farm deployment, and it stated clearly which outputs are attention cues and not diagnoses. Future work includes clinical validation through field data collection, veterinary review and CMT/SCC comparison; scalable deployment and integration with cooperatives, GIS and laboratory systems; and continued improvement of the models through more clinical data, species refinement, better baselines and improved explainability.

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