



Rapid Colorimetric and Artificial Intelligence-Based Methods for Determining the Microbial Quality of Raw Milk, Processed Milk, and Milk Products

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Abstract: Milk is a nutrient-rich food that can support microbial growth when hygienic handling, storage, or processing conditions are inadequate. Conventional microbiological tests remain important reference methods, but they can require substantial time, laboratory resources, and skilled handling. This review examines rapid colorimetric approaches and artificial intelligence (AI)-based methods for screening microbial quality in raw milk, processed milk, and milk products. Particular attention is given to dye-reduction assays such as resazurin, objective RGB colour measurement, machine-learning classification, and sensor systems such as electronic noses. Published studies indicate that colourimetric sensing can convert biochemical activity into measurable optical changes, while machine learning can associate sensor patterns with reference microbial measurements. One recent study using an RGB colourimetric resazurin assay reported 100% prediction accuracy for a low-microbial-concentration class and 96% for a high-microbial-concentration class, with lower performance in the intermediate class. Another study combining electronic-nose measurements with an artificial neural network reported very strong agreement between predicted and reference total bacterial counts in its tested and validated subsets. These findings support the potential of integrated sensing and AI as rapid screening tools, while also showing the need for representative datasets, controlled measurement conditions, external validation, and explainable decision systems. The proposed framework combines rapid colour sensing, reference microbiology, machine learning, and quality classification to support faster dairy-quality monitoring.

Keywords: milk quality, microbial quality, colorimetric assay, resazurin, RGB sensing, artificial intelligence, machine learning, electronic nose, dairy safety

I. INTRODUCTION

Milk and milk products are important foods because they provide proteins, fats, carbohydrates, minerals, vitamins, and other bioactive components. At the same time, their composition makes milk a favourable medium for the growth of microorganisms. Microbial activity can alter sensory properties, shorten shelf life, affect nutritional quality, and create food-safety concerns. Consequently, microbiological quality control is a central component of dairy processing and distribution. Reviews of rapid milk-quality technologies describe a broad range of sensor approaches based on pH, conductivity or impedance, dissolved oxygen, carbon dioxide, ATP, volatile compounds, colour indicators, electronic noses, and electronic tongues. [1], [9]

Traditional culture-based microbiological analysis is valuable because it provides established quantitative information, but it is not ideal for every real-time decision point. Recent reviews note that conventional approaches can be time-consuming, labour-intensive, and comparatively difficult to deploy for rapid screening. This has encouraged development of faster methods that can be used at collection, processing, storage, or distribution stages. [1], [9]

Colorimetric methods are attractive because microbial metabolism can cause a visible or measurable change in a chemical indicator. In dye-reduction assays, the colour response can be recorded visually or by an optical sensor. Digital RGB measurements can make this response more objective and provide numerical features for statistical or machine-learning models. A 2023 International Dairy Journal study demonstrated this concept using a resazurin assay, an RGB colour sensor, and machine learning to predict the microbiological quality of raw milk. [2]

Artificial intelligence provides a second layer: instead of relying only on a single colour threshold, a model can learn relationships among multiple sensor features and reference microbial measurements. Similar principles have been applied to electronic-nose systems. A Journal of Dairy Science study combined electronic-nose measurements with an artificial neural network to predict total bacterial count (TBC) in milk and reported strong predictive agreement in its test and validation subsets. [3]



The objective of this paper is to review rapid colorimetric and AI-based approaches for determining microbial quality in raw milk, processed milk, and milk products; compare their operating principles and limitations; and propose an integrated framework that can support rapid screening while retaining reference microbiological testing for calibration and validation.

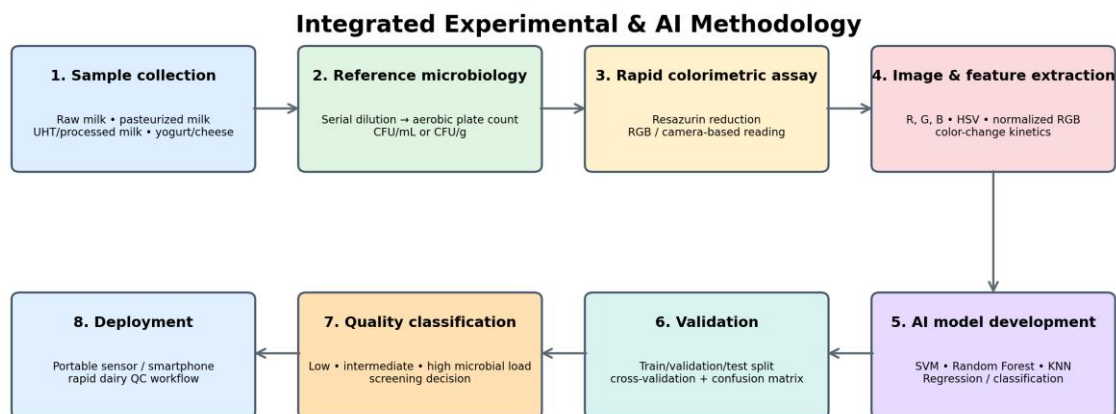


Figure 1. Conceptual workflow for rapid milk microbial-quality screening.

II. LITERATURE REVIEW

Rapid sensing for milk quality has developed around the need for faster, sensitive, cost-effective and easy-to-use systems. Poghossian et al. reviewed chemical sensors, biosensors, electronic noses, electronic tongues, wireless sensors and colour indicators for milk spoilage monitoring. Their review highlights the possibility of measuring indicators associated with microbial growth, including pH, impedance, ATP, oxygen, carbon dioxide and volatile compounds. [1]

Thanasirikul et al. specifically investigated an RGB-colourimetric resazurin method for raw milk. Their experiment used 102 raw-milk samples with different microbial concentrations. Colour measurements in red, green and blue channels were associated with microbial concentration, and a support-vector-machine model was evaluated for quality prediction. The reported accuracy was 100% for samples in the low microbial concentration class and 96% for the high class, while the intermediate class was more difficult to predict. This result illustrates both the potential and the importance of class boundaries and representative data. [2]

The colourimetric approach can also be extended beyond a single dye-reduction test. A 2024 Food Chemistry: X study described a colourimetric sensor array for rapid distinction and detection of psychrophilic bacteria in raw milk using modified gold nanoparticles and machine learning. The authors reported a detection limit of 10^2 CFU/mL and used linear discriminant analysis to distinguish bacterial types. Such sensor arrays illustrate how multiple colour responses can encode richer information than one visual endpoint. [5]

Electronic-nose systems provide another AI-compatible sensing route. Yang et al. developed an electronic-nose and artificial-neural-network method for TBC prediction. The reported qualitative model achieved 100% accuracy for its high, medium and low TBC categories on the testing and validation subsets, while the quantitative model showed R^2 values above 0.99 against reference values in those subsets. These are study-specific results and should not be interpreted as universal performance across all milk types or operating conditions. [3]

More recent work indicates a wider move toward AI-enabled dairy quality assessment using sensing, machine vision and multimodal data. A 2026 review identifies opportunities for AI in raw milk, milk powder, cheese and yogurt while also emphasizing challenges such as data scarcity, model generalization, cross-instrument transferability and explainability. A 2026 systematic study of conventional, sensor-induced and machine-learning methods further reflects the growing interest in combining sensing and data-driven analysis for milk quality. [7], [8], [10]

Overall, the literature suggests a complementary relationship: reference microbiology supplies reliable labels, rapid sensors provide fast measurements, and AI models can transform multi-dimensional sensor data into quality predictions. However, the literature also indicates that model performance is dependent on sample diversity, sensor stability, environmental control, preprocessing, and validation. [1], [7], [8]



III. METHODOLOGY

This paper follows a structured literature-based research methodology. The objective is to synthesize evidence on rapid colorimetric sensing and AI-based microbial-quality assessment rather than to claim a new laboratory validation experiment. The provided research-paper structure requires the methodology to explain the research design, data collection, tools, sampling, and analysis approach.

III-A.

RESEARCH

DESIGN

A descriptive and comparative review design was adopted. Peer-reviewed research and authoritative biomedical/database records were examined for methods involving rapid microbial detection, colourimetric assays, RGB sensing, electronic noses, machine learning and dairy-quality assessment. The evidence was organized according to sensing principle, data type, AI method, application area, reported performance and limitations.

III-B.

DATA

COLLECTION

Secondary data were used. Relevant literature included research articles and reviews covering rapid milk-quality sensors, resazurin/RGB colourimetric testing, electronic-nose systems, colourimetric sensor arrays, and AI-enabled dairy quality assessment. Key information extracted from each source included sample type, sensing mechanism, reference microbiological method, machine-learning approach, reported performance and practical limitations. [1], [2], [3], [5], [7]

III-C.

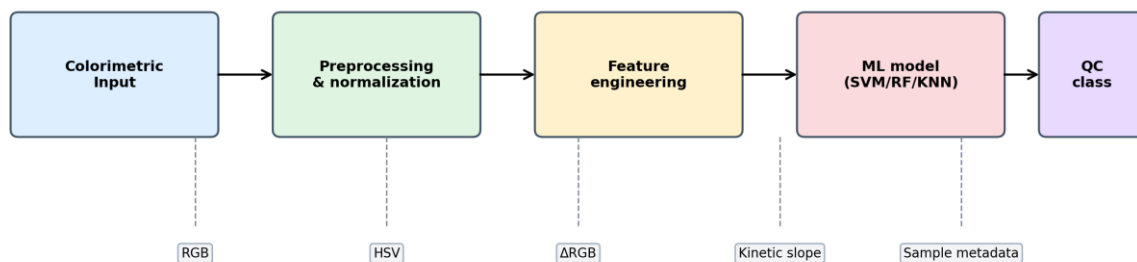
PROPOSED

INTEGRATED

METHOD

The proposed framework begins with representative milk sampling from raw milk, processed milk, or a milk product. A rapid colourimetric reaction or sensor measurement is then performed under controlled conditions. For a colourimetric route, the response can be captured by an RGB sensor or standardized camera system. The resulting numerical features are cleaned and normalized before being supplied to a machine-learning model. Reference microbial measurements, such as aerobic plate counts or total bacterial counts, provide target labels for model training and validation. The final output is a screening category or predicted microbial-load range. [2]

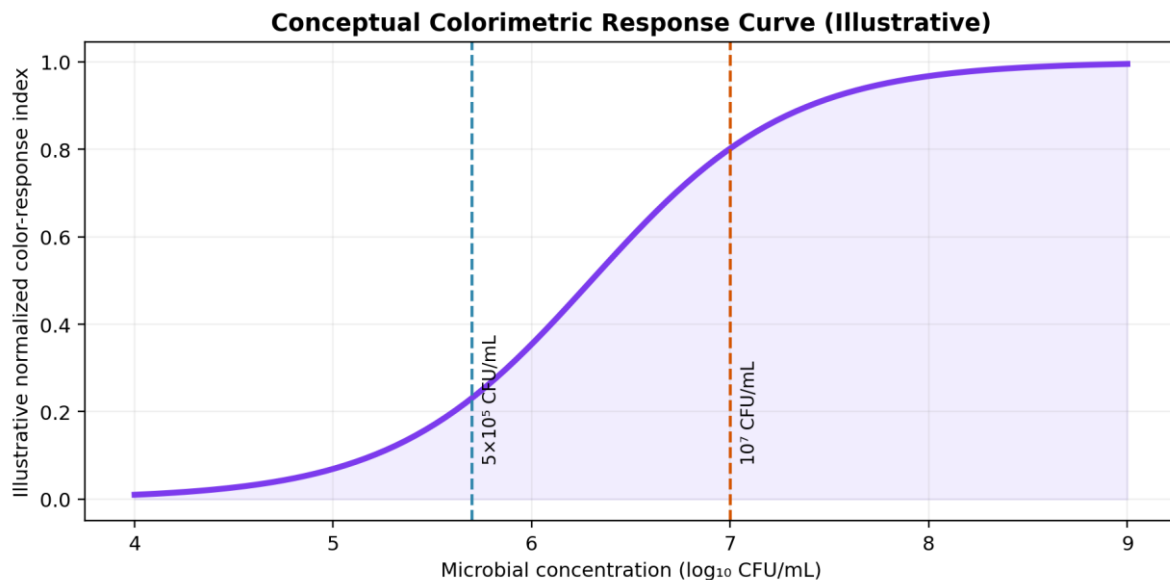
AI-Based Colorimetric Decision Pipeline



Output: predicted microbial-quality class / estimated microbial load

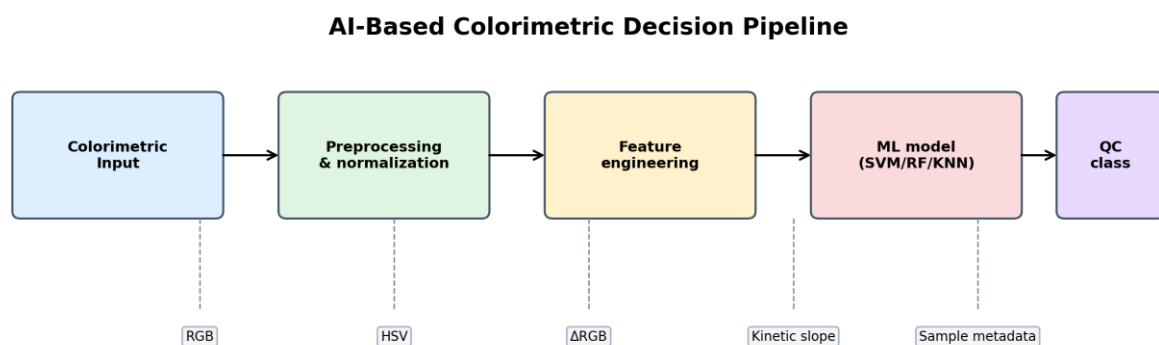
Important: AI is a screening layer; confirmatory microbiological testing remains necessary.

Figure 2. Conceptual colourimetric principle based on a dye-reduction response.



Illustrative relationship for methodology design; not experimental measurements.

Figure 3. Illustrative colourimetric response relationship. The curve is conceptual and not experimental data.



Output: predicted microbial-quality class / estimated microbial load

Important: AI is a screening layer; confirmatory microbiological testing remains necessary.

Figure 4. Proposed AI pipeline for sensor-based microbial-quality prediction.

III-D. AI AND DATA ANALYSIS

Possible supervised-learning approaches include support vector machines, decision trees, random forests, artificial neural networks and other regression/classification models. Classification can divide samples into predefined microbial-quality classes, while regression can estimate a continuous microbial-load value. Model development should separate training, validation and independent testing data to reduce optimistic performance estimates. Performance should be reported using appropriate metrics such as accuracy, precision, recall, F1-score, sensitivity, specificity, mean absolute error and coefficient of determination, depending on the task. [2], [3], [5]

III-E. SAMPLING AND QUALITY CONTROL

A robust future experimental study should include multiple batches, farms or suppliers, different seasons, relevant processing conditions, storage temperatures, and a range of microbial loads. Sensor measurements should be repeated, and reference microbiological analysis should be performed using an established laboratory method. Lighting, sample



temperature, reagent concentration, reaction time and sensor distance should be controlled for colourimetric imaging. For electronic noses, sensor drift, humidity, temperature and headspace equilibration should also be controlled. [1], [7], [8]

III-F. ETHICAL AND PRACTICAL CONSIDERATIONS

The framework is intended for quality screening and process monitoring. A rapid AI prediction should not automatically replace regulatory or reference microbiological testing unless the complete system has been validated for the intended product, population, operating range and regulatory requirements. False negatives are particularly important in food safety, so decision thresholds should be established using validated risk-based criteria. [1], [7]

IV. RESULTS

Because this paper is a literature-based review and not a newly conducted laboratory experiment, the Results section summarizes reported findings from published studies rather than presenting invented experimental measurements. This distinction is important when interpreting numerical performance values. The supplied research-paper format recommends objective presentation of findings through tables, graphs and statistics where applicable.

Table 1. Comparison of conventional, rapid sensing and AI-assisted approaches.

Method	Typical role	Strength	Limitation
Culture / plate count	Reference microbial enumeration	Established reference approach	Laborious and time-consuming [1], [9]
Colorimetric assay	Rapid screening via colour response	Simple, visual, low-cost potential	Colour can be affected by matrix/lighting; requires validation [1], [2]
RGB sensor / imaging	Objective colour measurement	Reduces subjective visual judgement	Needs controlled imaging/sensing conditions [2], [5]
E-nose + AI	Volatile-pattern based prediction	Rapid, non-destructive potential	Sensor drift and dataset generalization challenges [3], [4]
Colorimetric + AI	Integrated rapid microbial-quality prediction	Combines simple sensing with data-driven classification	Needs calibrated datasets and external validation [2], [5], [7]

IV-A. REPORTED COLORIMETRIC-AI FINDINGS

The RGB-resazurin study is a direct example of combining a rapid colour reaction with machine learning. It evaluated 102 raw-milk samples and created a dataset linking RGB colour measurements with microbial concentrations. The reported support-vector-machine model achieved 100% accuracy for the low microbial concentration class and 96% for the high class, but the intermediate class was less accurately predicted. [2]

This pattern is important because practical quality systems often have a difficult transition region. Samples near a threshold may have similar sensor responses, and a model trained only on clearly separated classes may perform less reliably around the boundary. Therefore, future systems should include many samples around decision thresholds and should report confusion matrices and class-specific sensitivity rather than relying only on overall accuracy. [2]



Literature-Derived SVM Benchmark for Raw Milk Screening

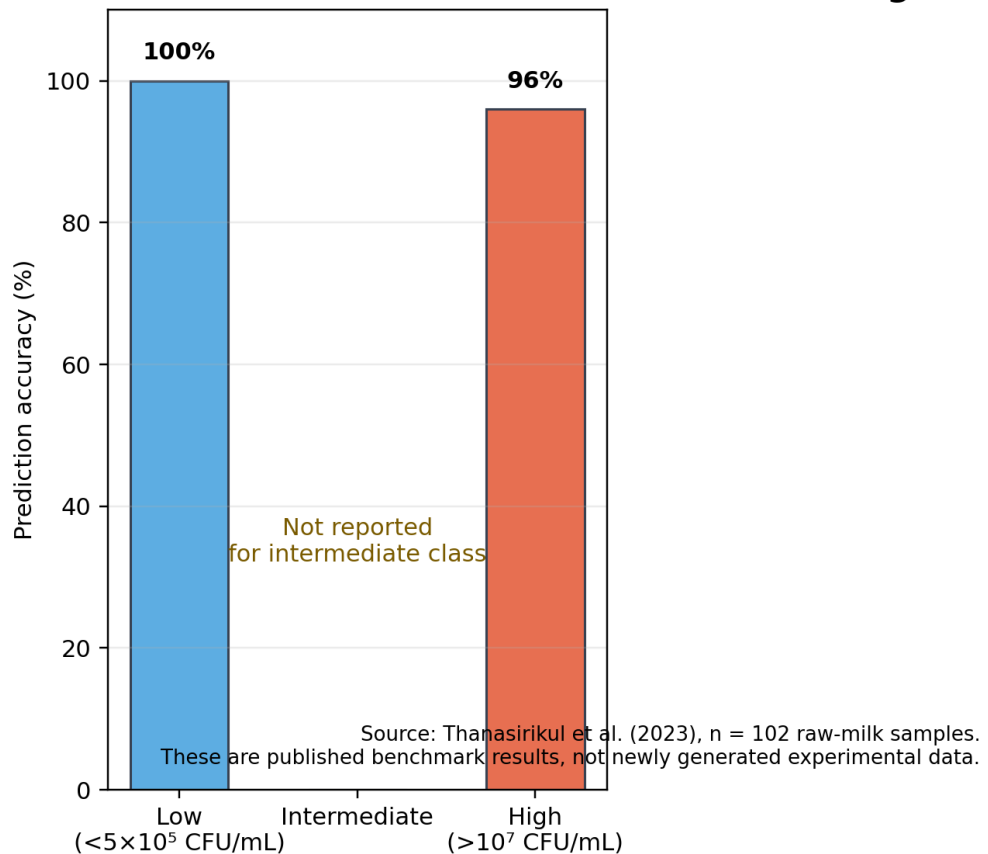


Figure 5. Literature-derived SVM benchmark for raw-milk microbial-quality classification.

IV-B. REPORTED E-NOSE AND AI FINDINGS

The electronic-nose plus artificial-neural-network study reported 100% qualitative classification accuracy for high, medium and low TBC groups in its testing and validation subsets. Its quantitative model reported R^2 values greater than 0.99 against reference values, with low mean relative differences in the reported subsets. The authors proposed potential use for rapid or online microbial-quality monitoring. [3]

IV-C. EMERGING SENSOR ARRAYS

The 2024 colourimetric sensor-array study demonstrated that multiple optical responses can be used to distinguish psychrophilic bacteria in raw milk and reported a 10^2 CFU/mL detection limit. The study illustrates how sensor arrays combined with pattern-recognition methods may provide both detection and discrimination information. [5]

IV-D. SMARTPHONE-ASSISTED SENSING

A 2024 study on smartphone-assisted optoelectronic sensing used a colourimetric sensor array and decision-tree rules for monitoring milk freshness. The reported evaluation included 20 milk samples, and the overall error rate was 3%, although a particular intermediate TBC range showed a higher error rate. This again indicates that rapid systems may perform differently across microbial-load ranges. [4]

V. DISCUSSION

The reviewed evidence supports a general concept in which rapid sensing and AI are complementary rather than competing technologies. The sensor converts microbial activity or its chemical consequences into a measurable signal, while the AI model interprets combinations of signals that may be difficult to translate into a single manual threshold. This can potentially reduce subjective colour assessment and support rapid screening at multiple points in the dairy supply chain. [1], [2], [3]



For raw milk, rapid screening can be useful because microbial quality may vary with animal health, farm hygiene, milking practices, cooling, transport and storage. A rapid sensor at collection or receiving points could support faster segregation of samples for further testing. For processed milk, the same concept can be used for process verification and detection of unexpected deterioration during storage. For milk products such as yogurt, cheese or other dairy foods, the sensor chemistry and model must be adapted to the product matrix because opacity, fat, acidity, colour, texture and volatile composition can influence measurements. [1], [2]

The main advantage of colourimetric systems is their conceptual simplicity. A visible chemical response can be measured with inexpensive optical hardware, and RGB values can be processed digitally. The main challenge is standardization. Illumination, camera characteristics, sample background, temperature, reaction time and matrix effects can change the measured colour even when microbial concentration is similar. Therefore, a deployable system should use controlled illumination or calibrated sensing hardware and include quality-control checks. [1], [2], [5]

AI adds predictive capability but introduces a data-quality dependency. A model may perform well in the laboratory and then lose accuracy when used with a new camera, sensor, milk variety, geographic source, season or storage condition. Recent AI-focused dairy reviews specifically identify data scarcity, generalization, cross-instrument transferability and explainability as important challenges. [7], [8], [10]

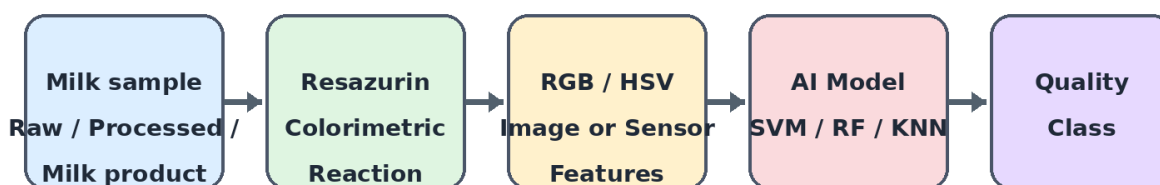
Another important issue is explainability. Food-quality personnel may need to understand why a sample has been classified as high risk. Simple models such as decision trees can provide more interpretable rules, while more complex neural networks may require feature-attribution or uncertainty techniques. A practical system should therefore provide not only a prediction but also a confidence/uncertainty indicator, sensor-quality status and an instruction for confirmatory laboratory testing when the sample is near a decision boundary. [7], [10]

The literature also suggests that no single rapid sensing technology is universally optimal. Electronic noses measure volatile patterns and can be highly sensitive to spoilage-related changes; colourimetric systems measure chemical/optical responses; spectroscopy and machine vision can capture additional information. A multimodal system could combine these signals, but increased complexity, calibration requirements and cost must be considered. [1], [7], [9]

V-A. PROPOSED PRACTICAL ARCHITECTURE

A practical architecture can be organized into five layers: (1) sample acquisition, (2) rapid sensing, (3) data preprocessing, (4) AI inference, and (5) quality-control action. The first layer defines sampling and handling; the second obtains colour or sensor measurements; the third removes noise and standardizes features; the fourth predicts microbial quality; and the fifth determines whether the sample is accepted for routine processing, held for confirmation, or referred for laboratory analysis.

Rapid Milk Microbial Quality Decision Framework



Reference: Aerobic Plate Count (APC)

Calibration + validation + confirmatory microbiology

Figure 6. Proposed practical architecture for rapid screening with confirmatory testing.

VI. CONCLUSION

Rapid colourimetric sensing and artificial intelligence provide promising approaches for faster assessment of microbial quality in milk and dairy products. The literature demonstrates that biochemical colour changes can be converted into objective RGB measurements and associated with reference microbial concentrations using machine-learning models. Electronic-nose systems similarly show that volatile patterns can be interpreted by neural networks to estimate total



bacterial count. Published studies report strong performance under their respective experimental conditions, but those results are study-specific and should not be generalized without external validation. [2], [3]

The most appropriate role for these technologies is currently rapid screening and decision support. Their value is greatest when they reduce the time between sampling and quality information while maintaining a pathway to confirmatory laboratory testing. [1], [7]

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