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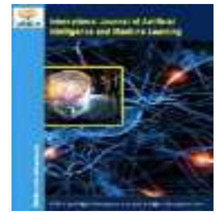

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AI for Sugarcane Stem Node Quality Assessment and Bud Germination Suitability: A Review

Madhuri S. Magar[1,2] Dr. Pooja A. Bagane[3]*

[1] Research Scholar, Faculty of Engineering, Symbiosis Institute of Technology (SIT), Symbiosis International (Deemed University) (SIU), Lavale, Pune – 412115, Maharashtra, India
[2] Department of Computer Science and Business Systems,
Kolhapur Institute of Technology's College of Engineering (Empowered Autonomous), Kolhapur – 416234, Maharashtra, India. E-mail: madhurimagar333@gmail.com ORCID ID: 0009-0005-7324-1547
[3] Faculty of Engineering, Symbiosis Institute of Technology (SIT), Symbiosis International (Deemed University)(SIU), Lavale, Pune – 412115, Maharashtra, India. E-mail: pooja.bagane@sitpune.edu.in, ORCID ID:0000-0001-9611-9601

Abstract
Sugarcane (Saccharum officinarum L.) is propagated vegetatively through stem cuttings ("setts") containing nodes that each bear a lateral bud, making stem node quality and bud germination suitability first-order determinants of field establishment and eventual cane yield. Commercial seed-cane selection still relies predominantly on manual visual inspection, a process that is subjective, labour-intensive, difficult to scale, and blind to sub-surface defects. This review synthesizes the current state of sensing technologies (RGB, multispectral, hyperspectral, thermal, X-ray/CT, 3D, and acoustic sensing) and artificial intelligence methods (traditional machine learning, deep learning-based detection and segmentation, transfer learning classification, vision transformers, and multimodal fusion) that could be applied, or have begun to be applied, to sugarcane stem node quality assessment and germination-suitability prediction. Dataset and annotation practices, regional deployment contexts spanning manual and mechanized seed-cane systems, and an integrated sensor-method-application framework are discussed. Persistent challenges include the absence of public sugarcane node/bud datasets, the difficulty of defining an objective ground truth for germination suitability, environmental variability affecting sensor readings in field conditions, and the interpretability of deep learning-based grading decisions. The review concludes by identifying a specific research gapthe lack of an integrated, annotated-dataset-driven, AI-based system for combined node quality assessment and germination-suitability classification that motivates need for research in dataset construction, model development, and systematic performance evaluation.

Keywords: Sugarcane; stem node; bud germination; seed-cane quality; machine vision; deep learning; precision agriculture

1. Introduction

Sugarcane is one of the most economically significant industrial and bioenergy crops in the world, forming the principal raw material for sugar, ethanol, and bagasse-based products across more than ninety producing countries [5]. Sugarcane is an important source of income and livelihood for farming communities, particularly across Asia, Latin America, and Africa, while global production is concentrated in a few major producing countries. Brazil, India, and Thailand are projected to remain the leading contributors to global sugarcane production, with Brazil and India alone accounting for approximately 60% of global output by 2034 [5]. Unlike cereal crops that are predominantly propagated through true botanical seed, commercial sugarcane (*Saccharum* spp.) is conventionally propagated vegetatively using pieces of stalk known as "setts" or seed cane, each containing nodes with axillary buds capable of developing into new shoots [3]. The successful sprouting of sugarcane buds and subsequent tiller development are critical components of early crop establishment, influencing stand density, the formation of millable canes, and ultimately cane and sugar yield [8]. Consequently, the quality of the seed-cane nodeincluding bud viability, moisture status, mechanical integrity, and freedom from pest or pathogen damageis an important early quality-control attribute in the sugarcane production cycle [8,19].

Despite its importance, node and bud quality assessment in commercial and smallholder practice continues to rely overwhelmingly on manual visual inspection performed by field staff or nursery workers [35]. This reliance on human judgement introduces well-documented limitations: grading is subjective and may be inconsistent across individual graders and inspection sessions, while manual inspection is labor-intensive,time-consuming, and difficult to scale to the throughput required by large nurseries and mechanized planting operations. Moreover, conventional visual inspection has limited ability to identify internal or sub-surface defects that do not produce discernible external symptoms, highlighting the need for objective and non-destructive approaches to sugarcane planting-material assessment [38,17].

Machinal domains concerned with the quality assessment of vegetatively propagated and seed-based planting materialparticularly potato tubers and cereal seedshave increasingly adopted machine vision, multispectral/hyperspectral sensing, machine learning, and deep learning for automated defect detection, classification, grading, and quality evaluation [4,10,18]. Likewise, the broader crop pest and disease detection literature has advanced substantially, particularly in leaf-, fruit-, and grain-level analysis using RGB, multispectral, and hyperspectral imaging integrated with convolutional neural networks and, more recently, transformer-based architectures [6,15,28,31]. These developments demonstrate the potential of deep-learning-based visual classification for agricultural quality assessment. Recent work by Gavali and Banu has further demonstrated the use of deep-learning architectures for image-based species classification [2,12], while Gavali et al. have investigated hybrid deep-learning fusion for combining information from multiple modalities [37]. Although these studies address different application domains, their methodological principlesfeature learning, multimodal fusion, and automated classification—are relevant to the development of intelligent agricultural inspection systems.

At present, existing reviews of AI applications in sugarcane have primarily concentrated on field- and canopy-level applications, including disease and pest detection, remote sensing-based crop health monitoring, yield estimation, varietal classification, and crop-management decision support [9,34]. These reviews provide substantial coverage of sensing modalities, machine-learning methods, remote-sensing platforms, and field-level deployment considerations, but do not specifically synthesize AI-based assessment of pre-planting sugarcane seed material at the individual stem-node and bud level. Consequently, a focused synthesis addressing node/bud imaging, quality attributes, germination-suitability prediction, dataset development, annotation practices, model architecture, and deployment considerations remains warranted [9,34]. This gap is significant because seed-cane quality assessment occurs at a distinct point in the production chain—typically in nurseries, seed-multiplication programs, or at the point of mechanized cutting—with its own sensing constraints, including small high-throughput objects and short inspection windows on sorting lines, as well as its own labelling challenge. Germination suitability can only be confirmed with certainty after a multi-week growth trial, creating a substantial gap between easily observed visual features and the true biological outcome of interest.

This review addresses that gap by:

(i) surveying the sensing technologies applicable to stem-node and bud inspection, including their principles, advantages, and limitations;

(ii) reviewing machine-learning and deep-learning methods relevant to node detection, quality classification, and germination-suitability prediction;

(iii) examining dataset construction and annotation practices specific to this domain, including the public datasets available for transfer learning;

(iv) discussing the regional and operational contexts spanning manual sett-cutting and mechanized billet-planting systems in which such technologies would need to be deployed;

(v) proposing an integrated sensor–method–application framework; and

(vi) identifying the technical, data-related, and practical deployment challenges that must be resolved, together with promising future research directions.

The review is structured to progressively build from crop biology, through sensing and algorithms, system-level deployment.

2. Literature survey

Recent advances in agricultural automation have demonstrated the potential of machine vision, machine learning, and deep learning for rapid and non-destructive assessment of crop and planting materials. In sugarcane, conventional propagation uses stalk setts containing axillary buds, and successful bud sprouting is an important determinant of crop establishment and subsequent yield [3,8]. However, assessment of bud and node quality is still largely dependent on manual visual inspection, which is subjective, labour-intensive, time-consuming, and difficult to scale [35,38]. Recent studies have therefore explored automated sugarcane bud detection and cutting using computer vision and deep-learning-based object detection, demonstrating the feasibility of real-time bud localization and automated seed-material preparation [38].

Machine vision has also been widely investigated for seed-quality assessment. Studies on soybean and other agricultural products have demonstrated the use of morphological,colour, texture, and spectral features for evaluating physical quality, viability, vigour, and defects [18,35]. Similarly, multispectral and deep-learning approaches have achieved promising results in agricultural defect detection [4]. Reviews of artificial intelligence in agriculture further indicate increasing adoption of CNNs, YOLO-based detectors, transfer learning, and transformer architectures for crop classification, disease detection, and quality assessment [6,15,23,28,36]. These developments provide a strong methodological foundation for automated sugarcane node inspection.

Different sensing technologies offer complementary information. RGB imaging is suitable for detecting visible characteristics such as bud morphology, colour, surface damage, and structural defects, whereas multispectral, hyperspectral, thermal, and other non-destructive techniques may provide additional information related to moisture, tissue condition, disease, and internal quality [4,22,25]. Deep learning is particularly promising because it can automatically learn discriminative features from images and reduce dependence on manually engineered features. Transfer learning can further address the problem of limited domain-specific datasets [36]. Recent work by Gavali and Banu on DQFCNN and optimized hybrid deep learning for image classification demonstrates the potential of specialized and optimized deep-learning architectures [2,12]. Gavali et al. have also investigated hybrid deep-learning fusion for multimodal data [12], providing methodological support for combining complementary information in intelligent classification systems.

Despite these advances, a clear research gap remains in pre-planting sugarcane node and bud quality assessment. Existing sugarcane studies primarily focus on bud detection, cutting, field monitoring, disease detection, and crop-level applications [9,34,38], while seed-quality studies largely concern cereal seeds and other agricultural products [13,18,35]. As summarized in Table 1**,** these studies demonstrate the potential of machine vision, image processing, machine learning, deep learning, and multimodal approaches, but limited research has systematically integrated node/bud imaging, quality attributes, germination-suitability prediction, dataset development, deep-learning models, and practical deployment into a unified framework. Therefore, a focused review of sensing technologies, image-processing methods, machine-learning/deep-learning approaches, datasets, annotation strategies, and deployment challenges is necessary to advance automated and objective sugarcane planting-material quality assessment.

Table 1: Summary of Selected Literature on AI-Based Quality Assessment

No.	Paper Title	Author(s)	Methods Used	Key Limitation
1	Sugarcane pre-sprouted seedlings: A novel method for sugarcane establishment	Otto et al. (2022)	Pre-sprouted seedlings; field evaluation	Requires controlled nursery conditions and additional management
2	Effects of planting pre-germinated buds on stand establishment in sugarcane	Madala et al. (2023)	Pre-germinated buds; stand-establishment analysis	Limited automated assessment of individual bud quality
3	Machine vision based alternative testing approach for physical purity, viability and vigour testing of soybean seeds	Das et al. (2018)	Machine vision; image features; classification	Focused on soybean seeds, not sugarcane nodes
4	Smart vision-based sugarcane bud detection and cutting system for seed generation	Kumar et al. (2025)	YOLO-based detection; machine vision; automated cutting	Mainly detects/cuts buds; does not predict germination suitability
5	Automatic detection of multi-type defects on potatoes using multispectral imaging combined with a deep learning model	Yang et al. (2022)	Multispectral imaging; deep learning	Potato-specific; multispectral equipment increases system complexity
6	Optimized wheat seed classification using YOLO with morphological image feature enhancement	Deepika et al. (2026)	YOLO; morphological features; deep learning	Developed for wheat seeds; limited cross-crop generalization
7	Seed identification using machine vision: Machine learning features and model performance	Himmelboe et al. (2025)	Machine vision; ML features; classification	Primarily seed identification rather than germination prediction
8	Artificial intelligence-based tools for next-generation seed quality analysis	Mishra et al. (2025)	AI; machine vision; deep learning	Highlights data and validation challenges; limited sugarcane-specific studies

9	Deep learning and computer vision in plant disease detection: A comprehensive review	Upadhyay et al. (2025)	CNN; computer vision; deep learning	Mainly disease-focused rather than planting-material quality
10	Agricultural object detection with YOLO algorithm: A bibliometric and systematic literature review	Badgujar et al. (2024)	YOLO; object detection; systematic review	General agricultural applications; limited sugarcane-node focus
11	Transfer learning in agriculture: A review	Hossen et al. (2025)	Transfer learning; CNN/deep learning	Performance depends strongly on source and target datasets
12	Vision transformers in precision agriculture: A comprehensive survey	Lin et al. (2025)	Vision Transformer; attention mechanisms	Requires relatively large datasets and computational resources
13	DQFCNN: A new deep learning architecture for bird species classification based on images	Gavali& Banu (2025)	CNN; deep feature learning; image classification	Bird-specific dataset; generalization to agricultural objects requires validation
14	Energy Valley Flamingo Search Optimization trained hybrid deep learning for bird species classification	Gavali& Banu (2025)	Optimization; hybrid deep learning; image classification	Computational complexity and application-specific validation

3. Biology and Quality Determinants of Sugarcane Stem Nodes

3.1 Node and Bud Anatomy Relevant to Germination

Each sugarcane stalk is composed of a series of nodes and internodes. A node bears a single axillary (lateral) bud positioned above a leaf scar, together with a root band a ring of root primordia immediately below the bud, and in many varieties a wax band or growth ring encircling the stalk[21]. The bud itself is protected by overlapping bud scales and contains the shoot apical meristem responsible for producing the primary shoot upon germination. The structural integrity and moisture status of the bud scales, the vascular connectivity between the bud and the surrounding stalk tissue, and the viability of the meristematic tissue jointly determine whether a node will successfully sprout [11]. These anatomical features bud shape, scale condition, root band prominence, and surface coloration constitute the visually and spectrally observable proxies that computer vision systems must learn to associate with underlying viability shown in figure 1.

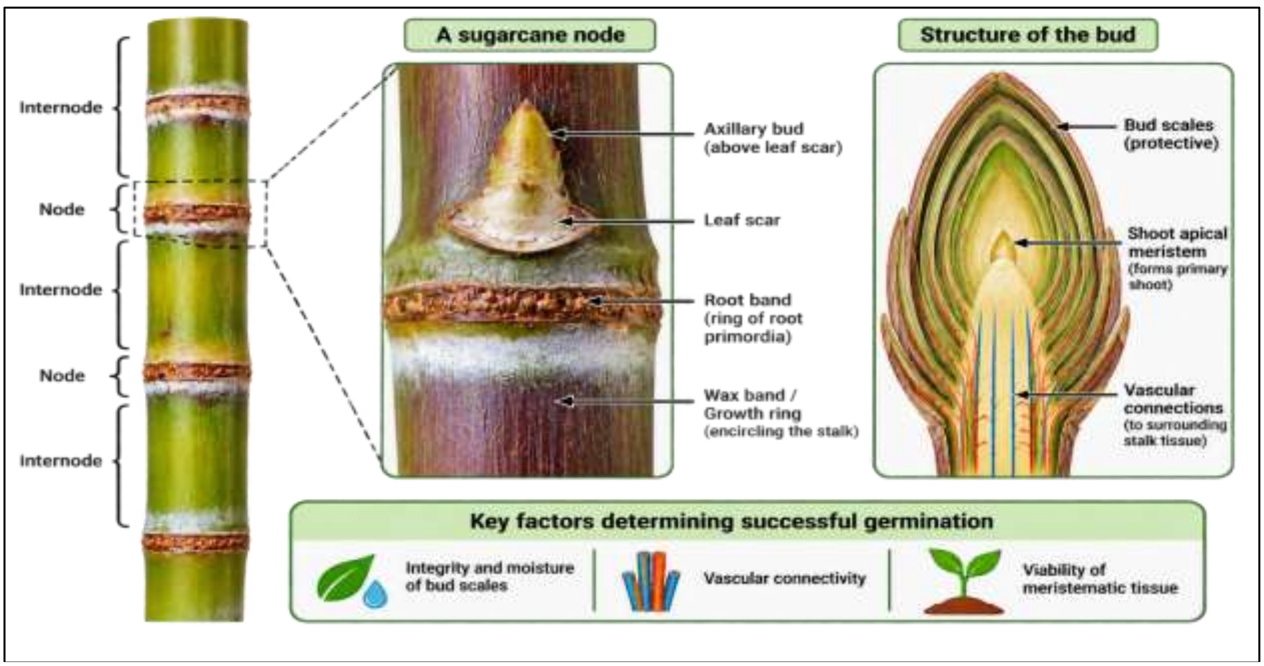

Figure 1. Sugarcane Stem Node and Bud Anatomy Related to Germination

3.2 Factors Affecting Bud Viability and Germination Suitability

Numerous agronomic and post-harvest factors influence whether a given node will germinate successfully, and these factors define the feature space that an intelligent assessment system must ultimately learn to interpret:

- **Varietal differences:** Bud size, dormancy characteristics, and germination vigour vary substantially among sugarcane cultivars. Therefore, quality-assessment models should either generalize across varieties or be calibrated for specific cultivars [11].
- **Node position on the stalk:** Top, middle, and basal nodes can differ in bud maturity, moisture reserves, and physiological condition, resulting in differences in germination performance [3,11].
- **Moisture content and desiccation:** Post-harvest moisture loss from cut setts can reduce bud viability and germination, particularly when planting is delayed or setts are exposed to high temperatures [24].
- **Mechanical damage:** Sugarcane buds are sensitive to cutting injury, and improper cutting can adversely affect subsequent germination. Studies on sugarcane bud chipping indicate that cutting speed, knife thickness, and stalk diameter influence bud damage, emphasizing the need to minimize mechanical injury during planting-material preparation [14].
- **Disease and pathogen infestation:** Diseases such as red rot and smut can be associated with infected sugarcane planting material. Red rot is commonly disseminated through infected setts, while infected vegetative material can contribute to the spread of smut. The use of healthy and disease-free planting material is therefore important for reducing pathogen transmission [19].
- **Pest infestation:**Internal insect-borer damage can affect the internal tissues of sugarcane stalks while remaining difficult to identify through external visual inspection. This highlights the potential value of non-destructive sensing techniques for detecting internal defects in planting material [19].
- **Storage duration and environmental exposure:**The duration and conditions of storage can influence the moisture status and germination performance of sugarcane bud setts. Therefore, storage history should be considered when developing automated germination-suitability models [18,24].
- **Cutting method:**Single-bud and multi-bud setts involve different planting-material configurations, while cutting systems can differ in cutting precision, bud damage, and processing efficiency. Therefore, cutting configuration and processing conditions should be considered when assessing node/bud quality and germination potential[15,19,20].

3.3 The Ground-Truth Definition Problem

A central methodological challenge for any AI-based node assessment system is the definition of an objective, reproducible ground truth for “quality” and “germination suitability.” Germination outcome can only be confirmed with certainty through a multi-week growth trial — the standard germination or sprouting test used in agronomic research[16]creating a substantial temporal and practical gap between the visual or spectral features that can be captured instantaneously on a sorting line and the true biological outcome those features are meant to predict. Consequently, most AI systems in this domain must be trained either on proxy labels (visually or spectrally assessed quality grades assigned by expert agronomists) or on outcome labels obtained from a subset of nodes tracked through to actual germination, with the two labelling strategies carrying different trade-offs in label reliability, dataset size, and time-to-collect. This distinction has direct implications for how a doctoral research program should structure its own data annotation protocol, discussed further in Section 6.

4. Sensors and Imaging Modalities for Node and Bud Assessment

Sensor selection is the foundational decision in any intelligent node assessment system, since it determines both the class of defects that can be detected and the downstream algorithmic requirements. This section surveys sensing modalities with established or plausible applicability to sugarcane stem node and bud inspection, drawing on analogous applications in crop pest detection and seed/tuber quality grading where sugarcane-specific evidence does not yet exist.

4.1 RGB Imaging and Machine Vision

RGB cameras remain the most widely deployed sensor in agricultural quality-grading systems owing to their low cost, ease of integration, and compatibility with both fixed sorting-line installations and handheld or smartphone-based field inspection [18].For sugarcane nodes, RGB imaging is well suited to detecting external defects such as discoloration, visible mechanical damage, surface lesions associated with disease, and gross bud malformation, and to performing node localization and counting along a stalk. Its principal limitation is an inability to detect sub-surface or sub-visual defects, and a sensitivity to variable field lighting, soil residue, and surface moisture that necessitates either controlled imaging enclosures or robust illumination-invariant preprocessing.

4.2 Multispectral and Hyperspectral Imaging

Multispectral and hyperspectral sensors extend measurement beyond the visible spectrum into the near-infrared and, for hyperspectral systems, across hundreds of contiguous narrow bands, enabling the detection of moisture content, pigment degradation, and early-stage physiological stress that precedes visible symptoms[13,22]. These properties are directly relevant to detecting desiccation-related bud mortality and to distinguishing visually similar but physiologically distinct nodes[22]. To the best of our knowledge, published validation of multispectral or hyperspectral sensing specifically for sugarcane stem-node or bud viability assessment remains limited, indicating a potential research opportunity.

4.3 Thermal Infrared Imaging

Thermal sensing exploits the relationship between metabolic activity and surface temperature; living, metabolically active bud tissue may exhibit subtly different thermal signatures from desiccated or necrotic tissue [25]. While this principle has been applied to detect insect clusters and plant stress in other cropping contexts, its application to sugarcane bud viability screening remains unexplored and would require careful control of ambient temperature and airflow to yield a reliable signal.

4.4 X-ray and Computed Tomography Imaging

X-ray and CT imaging are unique among the modalities considered here in their ability to directly visualize internal structure without physically sectioning the node, making them the only realistic non-destructive route to detecting internal borer damage, bud cavity collapse, or internal desiccation [27] Their high cost and specialized handling requirements currently confine such systems to laboratory research rather than field or commercial-line deployment, but they may serve a valuable role in generating high-fidelity ground-truth labels for training more deployable RGB- or spectral-imaging-based models.

4.5 Three-Dimensional and Laser Profiling

Structured-light, stereo-vision, or laser-triangulation systems can capture node geometry — diameter, internode spacing, and surface contour independent of lighting and color variation, supporting geometric grading criteria that complement color- and texture-based quality[29]. This modality is most naturally suited to mechanized billet-cutting lines where consistent sizing is itself a quality objective.

4.6 Acoustic and Vibration Sensing

Acoustic and vibration sensors, which have shown promise for detecting hollow or internally decayed material in stored grain and wood-boring pest contexts through analysis of induced vibration signatures [36], represent a low-cost, non-invasive candidate for screening sugarcane stalk sections for internal decay or borer damage prior to cutting, though this application has not yet been validated and would need to contend with substantial background noise in field or factory environments.

Table 2: Comparative summary of sensing modalities for sugarcane stem node and bud quality assessment.

Sensor Type	Detection Principle	Key Advantage	Core Limitation	Reported/Expected Accuracy	Cost Level	Best Use Case
RGB imaging / machine vision	Visible-light color imaging (380–780 nm) via CCD/CMOS sensors	Low cost, fast, easy to integrate into sorting lines and mobile/smartphone apps	Cannot detect sub-surface defects; sensitive to lighting variation and surface occlusion	Plausible: high, based on analogous crop-grading tasks [18]	Low	High-throughput external defect and node/bud localization on sorting lines
Multispectral imaging	Captures discrete spectral bands in visible/near-infrared	Reveals moisture and pigment-related stress not visible in RGB; moderate cost	Lower spectral resolution than hyperspectral; may miss subtle early-stage stress signatures	Not yet established for sugarcane nodes [13]	Medium	Assessing desiccation severity and general node health at nursery scale
Hyperspectral imaging	Continuous narrow-band spectral capture	Very high spectral resolution; potential for sub-	High cost; complex data processing;	Not yet established for sugarcane nodes [22]	High	Early, pre-visual detection of internal disease

Sensor Type	Detection Principle	Key Advantage	Core Limitation	Reported/Expected Accuracy	Cost Level	Best Use Case
	(typically 400–2500 nm)	visual disease/damage detection	sensitive to calibration and environment			or moisture stress in high-value seed-cane programs
Thermal infrared	Detects long-wave infrared radiation related to surface temperature	Non-invasive; can reveal metabolic activity differences between viable and non-viable buds	Susceptible to ambient temperature and airflow; limited spatial resolution	Largely unexplored for sugarcane buds — research gap [25]	Medium	Screening for latent bud desiccation or metabolic decline before visible symptoms appear
X-ray / CT imaging	Penetrating radiation reveals internal density variation	Only modality able to directly visualize internal hollowing, borer damage, or bud cavity integrity	High cost, specialized equipment, generally unsuited to field/line deployment	Demonstrated in analogous seed/kernel inspection contexts [27]; unexplored in sugarcane nodes	Very High	Laboratory-scale research quantification of internal bud/node integrity
3D / depth sensing and laser profiling	Structured light, stereo vision, or laser triangulation for surface geometry	Captures node diameter, internode length, and surface shape independent of color/lighting	Cannot assess internal or biochemical condition; adds system complexity	Unexplored for sugarcane — research gap [29]	Medium-High	Automated sizing and geometric grading on mechanized cutting lines
Acoustic / vibration sensing	Captures sound or vibration signatures from mechanical excitation or internal cavities	Potential for non-destructive detection of hollow or internally decayed stalk sections	Highly susceptible to environmental noise; largely unvalidated for this application	Unexplored for sugarcane nodes; analogous use in stored-grain pest detection [32]	Medium	Screening for internal decay or borer-hollowed sections prior to cutting

5. Artificial Intelligence and Machine Learning Methods

Following sensor selection, the choice of computational method determines how raw imaging or sensor data is converted into actionable node quality and germination-suitability decisions. This section reviews method categories in order of increasing model complexity and data requirements, framing each in terms of its applicability to the three sub-problems relevant to this domain: node/bud localization, quality classification, and germination-suitability prediction.

5.1 Traditional Machine Learning Approaches

Traditional machine learning pipelines for node quality assessment typically involve manual extraction of colour, texture, shape, or spectral-index features followed by classification using algorithms such as support vector machines, random forests, k-nearest neighbours, or partial least squares regression[1].These approaches remain attractive in early-stage research or resource-constrained deployment settings because they require comparatively small training datasets and produce classifications that are relatively interpretable in terms of the underlying visual or spectral features. Their principal limitation is a ceiling on achievable accuracy when the distinguishing features between quality grades are subtle or high-dimensional, as is plausible for early-stage bud desiccation or latent disease.

5.2 Deep Learning for Node and Bud Detection and Segmentation

Convolutional neural network-based object detectors provide the means to automatically localize individual nodes and buds along a stalk image, a necessary precursor to per-node quality classification. Two-stage detectors such as Faster R-CNN and Mask R-CNN offer high localization and, in the case of Mask R-CNN, pixel-level segmentation accuracy, at the cost of slower inference[1], while one-stage detectors from the YOLO family and SSD prioritize inference speed, making them attractive for real-time deployment on mechanized sorting or cutting lines [23]. Given that sugarcane nodes are small, closely spaced, and may be partially occluded by leaf sheath residue, detection performance is likely to depend heavily on backbone choice, anchor/scale configuration, and training data diversity considerations directly analogous to the small-object detection challenges documented in dense agricultural pest datasets.

5.3 Deep Learning for Quality Classification

Once a node or bud region has been localized, transfer learning using CNN backbones pre-trained on large-scale image corpora (e.g., ImageNet) and fine-tuned on node imagery offers an efficient route to quality classification with modest task-specific data requirements[33].More recently, Vision Transformer and hybrid CNN-Transformer architectures have demonstrated strong performance in agricultural image-analysis tasks involving complex visual patterns and fine-grained distinctions [6]a property plausibly shared by the task of distinguishing marginally viable from non-viable buds. The relative scarcity of sugarcane-specific training data makes transfer learning and data-efficient fine-tuning strategies particularly important considerations for this application.5.4 Multimodal and Sensor Fusion Approaches

Given that no single sensing modality captures the full range of factors affecting bud viability (external condition, internal integrity, moisture status, and storage history), multimodal fusion architectures that combine RGB imagery with spectral, thermal, or tabular environmental data represent a promising direction for improving classification robustness [33]. Such approaches introduce additional system complexity and data-synchronization requirements but may be essential for capturing sub-visual quality indicators that RGB imaging alone cannot resolve.

5.4 Germination-Suitability Prediction as a Distinct Modelling Problem

Germination-suitability prediction differs from node quality classification in that its target variable eventual sprouting successis inherently probabilistic and influenced by post-imaging factors such as storage duration, temperature history, and planting conditions. This motivates framing the problem as either a classification task (germinated/not germinated within a defined period) or a regression task (predicted germination percentage or vigor score), with inputs comprising node-level visual/spectral features augmented by storage-time and environmental-history variables. Gradient-boosted tree methods such as XGBoost and recurrent architectures such as LSTM or GRU networks are well suited to incorporating such time-varying covariates [36], drawing on analogous applications in crop pest population forecasting where temporal meteorological data is fused with static features to predict a future biological outcome.

Table 3: Summary of AI/ML method categories applicable to sugarcane node quality assessment and germination-suitability prediction.

Method Category	Representative Methods	Primary Task	Key Strength	Key Limitation
Traditional machine learning	SVM, Random Forest, k-NN, PLSR on hand-engineered color/texture/shape/spectral features	Node/bud quality classification from RGB or spectral features	Works with small datasets; interpretable features; low computational cost	Requires manual feature engineering; limited capacity for complex, high-dimensional patterns [1]
Two-stage deep object detectors	Faster R-CNN, Mask R-CNN and variants	Node/bud localization and instance segmentation along a stalk image	High localization accuracy; segmentation enables precise bud delineation	Higher computational cost; slower inference than one-stage detectors [1]
One-stage deep object detectors	YOLO series, SSD	Real-time node/bud detection and counting on sorting lines	Fast inference suited to real-time throughput requirements	Can trade off some accuracy for speed, particularly on small or occluded objects [23]
Transfer-learning classification	Fine-tuned ResNet, EfficientNet, VGG, MobileNet backbones	Node/bud quality grading (e.g., viable/non-viable, healthy/damaged categories)	Reduces data requirements by leveraging pre-trained features; well established in	Domain gap between source pre-training data and node imagery may require substantial fine-tuning data

Method Category	Representative Methods	Primary Task	Key Strength	Key Limitation
			crop image classification [36]	
Vision Transformers	ViT, Swin Transformer and hybrid CNN-Transformer architectures	Fine-grained bud health classification; global context modelling	Strong performance on complex, high-inter-class-similarity tasks [6]	Typically requires larger training datasets than CNNs; higher computational demand
Multimodal / sensor fusion	Fusion of RGB with spectral, thermal, or environmental data via CNN/attention-based fusion architectures	Combined external and physiological/biochemical quality assessment	Captures complementary information sources; potential for higher robustness [31]	Increased system complexity, cost, and data alignment/synchronization requirements
Time-series / tabular models for germination prediction	XGBoost, Random Forest, LSTM/GRU on node-feature-plus-storage-history data	Predicting germination probability or vigor score from node features and post-harvest history	Can incorporate temporal storage/environmental variables directly relevant to viability decline [36]	Requires longitudinal outcome data linking node features to actual germination results

6. Datasets and Data Annotation Practices

6.1 Public Datasets and Transfer Learning

No public, sugarcane-specific stem node or bud image dataset currently exists in the literature reviewed for this article, in contrast to the general crop pest detection domain, where large public benchmarks such as IP102 and PlantVillagehave substantially accelerated model development through pre-training and transfer learning. IP102 contains more than 75,000 images across 102 pest categories, with approximately 19,000 images additionally annotated with bounding boxes for detection. The PlantVillagedataset contains54,306 images of healthy and diseased plant leaves, covering multiple crop species and disease classes. The dataset has subsequently become a widely used benchmark for plant-disease image classification. In the absence of a sugarcane-specific benchmark, pre-training on such general agricultural image corpora, or on datasets from analogous vegetatively propagated crops (e.g., potato seed-tuber or cassava stem-cutting image collections, where these exist and are publicly available), represents a practical strategy for initializing model weights before fine-tuning on a smaller, task-specific sugarcane node dataset.

6.2 The Absence of a Public Sugarcane Node/Bud Dataset as a Key Gap

The lack of a publicly available, well-annotated sugarcane stem node and bud image dataset constitutes one of the most significant barriers to progress in this specific research area. Unlike leaf-disease or fruit-pest datasets, which benefit from large, visually distinctive, and relatively easy-to-photograph targets, node and bud imagery requires closer, more controlled acquisition (often macro-scale imaging) and depends on an accompanying, labor-intensive ground-truth determination process (destructive sectioning or multi-week germination trials) to establish reliable quality or viability labels. This dual burden specialized image acquisition plus costly label generationlikely explains the absence of an existing public benchmark and directly motivates the dataset-construction.

6.3 Recommended Practices for Self-Collected Dataset Construction

Based on established practices in analogous small-object, high-inter-class-similarity agricultural imaging tasks, the following practices are recommended for constructing a sugarcane node/bud dataset:

- Image acquisition setup: controlled or semi-controlled lighting, consistent camera-to-node distance, and inclusion of multiple varieties, node positions, and storage durations to ensure representativeness [28,31].
- Annotation protocol: a decision between bounding-box annotation (sufficient for detection/counting), pixel-level segmentation (needed for precise bud/eye delineation), and categorical quality-grade labelling (needed for classification), potentially combined in a multi-task annotation scheme.
- Ground-truth labelling strategy: a decision between bounding-box annotation (sufficient for detection/counting), pixel-level segmentation (needed for precise bud/eye delineation), and

categorical quality-grade labelling (needed for classification), potentially combined in a multi-task annotation scheme.
- Inter-annotator agreement: use of multiple trained annotators, ideally with agricultural expertise, and report an appropriate agreement statistic such as Cohen's kappa or Fleiss' kappa to quantify labelling reliability.
- Data augmentation: rotation, flipping, controlled brightness/contrast variation, and potentially GAN-based synthetic augmentation to address class imbalance between healthy and defective/non-viable nodes, mirroring augmentation strategies used in other small-object agricultural detection datasets
- Dataset splitting and generalization testing: Dataset splitting and generalization testing: variety-wise and/or region-wise train/test splitting, in addition to conventional random splitting, to explicitly evaluate cross-variety and cross-regional generalization.7. Applications Across Growing Regions and Seed-Cane Systems.

7. Applications Across Growing Regions and Seed-cane Systems

7.1 Manual Sett Cutting versus Mechanized Billet Planting

Sugarcane planting material is prepared and planted through a range of manual, semi-mechanized, and mechanized systems. In manual systems, stalks are distributed and cut into seed pieces or setts using hand tools, whereas mechanized systems may employ harvesters, billet cutters, or dedicated planting machinery to prepare and deliver billets or pre-cut seed pieces at substantially higher operational throughput [8]. Mechanized billet planting can reduce labour requirements and improve operational efficiency, although seed damage, billet quality, metering accuracy, and planting uniformity remain important considerations.These contrasting production environments impose different deployment constraints on an AI-based node-assessment system. Manual cutting operations may be better suited to portable, low-cost RGB-based inspection systems using handheld or smartphone cameras, whereas mechanized billet preparation and planting can benefit from inline, high-speed machine-vision systems capable of continuous assessment and automated rejection or grading. For such high-throughput applications, lightweight one-stage object-detection architectures and edge-deployable inference platforms may provide practical advantages in terms of processing speed and deployment cost.

7.2 Nursery and Seed-Cane Multiplication Programs

Certified seed-cane multiplication programs, which supply high-quality and disease-managed planting material to growers, represent a particularly suitable early deployment context for automated node-quality assessment because nursery production operates within defined seed-quality, varietal, disease, registration, and biosecurity requirements [26].In established seed-cane systems, certified planting material is used to establish registered nurseries, from which planting material is progressively multiplied for subsequent nursery and commercial production. Such systems place particular emphasis on planting-material health, varietal purity, germination, and quality assurance.This controlled quality-assurance environment makes nursery operations a logical initial deployment setting for AI-based node and bud assessment. Higher-cost sensing modalities, such as hyperspectral or X-ray imaging, may be more economically feasible in specialized nursery and seed-production facilities than in general commercial field operations because the primary objective is quality assurance of valuable propagation material rather than high-volume commodity inspection. Consequently, a staged deployment strategy could begin with RGB-based screening and subsequently incorporate multispectral, hyperspectral, or X-ray sensing where the additional information provides measurable improvements in germination prediction, disease detection, or internal quality assessment.

7.3 Regional Variation in Varieties, Climate, and Pest Pressure

Sugarcane is cultivated across diverse tropical and subtropical agroecological environments, with substantial variation in climatic conditions and pest and disease pressures among production regions [30].Models trained on node imagery from one region or limited variety set may not generalize reliably to other production environments. This concern is consistent with domain-shift challenges documented in agricultural image analysis, where differences in region, season, crop variety, illumination, and acquisition conditions can reduce model transferability. This underscores the importance of variety- and region-diverse dataset construction (Section 6.3) and suggests that transfer learning or domain-adaptation techniques may be necessary components of any system intended for multi-regional deployment.

8. Synergizing Sensors, Methods, and Applications

Building on the preceding sections, an integrated deployment framework can be proposed in which sensor choice, data structure, and algorithmic method are jointly determined by the specific deployment context:

- For portable, low-cost field or manual sett-cutting inspection: RGB imaging paired with a lightweight, transfer-learning-based CNN classifier or one-stage detector, prioritizing speed and low hardware cost over exhaustive defect coverage.
- For high-throughput mechanized billet-sorting lines: RGB and/or 3D/laser profiling combined with a real-time one-stage detector (e.g., a YOLO-family model) for simultaneous node localization, geometric grading, and coarse quality classification within the line's cycle time.
- For nursery and certified seed-multiplication programs: a layered approach combining RGB screening for gross defects with targeted multispectral or hyperspectral imaging of flagged nodes for sub-visual disease or desiccation confirmation, feeding a multimodal fusion classifier.
- For germination-suitability prediction specifically: node-level visual/spectral features combined with storage-duration and environmental-history data, processed through a tabular or time-series model (e.g., gradient-boosted trees or LSTM), trained against outcome labels obtained from tracked germination trials.

This layered, context-dependent framework mirrors approaches proposed in other precision-agriculture domains, where technology stacking is matched to the value, throughput, and risk profile of the specific application context rather than a single sensor-algorithm combination being applied uniformly across all deployment scenarios

9. Challenges and Future Research Directions

9.1 Data Scarcity and Annotation Cost

The absence of a public sugarcane node/bud dataset, combined with the high cost of generating reliable germination-outcome ground truth, represents the most immediate barrier to progress in this domain. Future work should prioritize the release of annotated benchmark datasets, potentially through multi-institutional collaboration, to enable comparable evaluation across research groups, as has occurred in the broader crop pest detection field following the release of datasets such as IP102 and Pest24.

9.2 Defining an Objective Ground Truth for Germination Suitability

The temporal gap between observable node features and confirmed germination outcome creates a persistent tension between label reliability and dataset scale. Future research should systematically compare proxy-label-trained models against outcome-label-trained models to quantify the practical cost, in terms of predictive accuracy, of relying on more easily obtained proxy labels.

9.3 Environmental Variability and Sensor Cost for Smallholders

Field lighting variability, dust, and moisture affect RGB and spectral sensor readings, while the cost of multispectral, hyperspectral, or X-ray equipment may be prohibitive for smallholder-scale deployment. Research into low-cost sensor alternatives, robust illumination-invariant preprocessing, and shared or service-based deployment models (analogous to drone-as-a-service concepts proposed in the broader precision agriculture literature) is needed to ensure equitable access to these technologies.

9.4 Interpretability of Deep Learning-Based Grading Decisions

The black-box nature of deep learning models presents an adoption barrier where farmers, nursery operators, or certification bodies must trust and act upon automated grading decisions. Integration of explainability techniques such as class activation mapping, attention visualization, or SHAP-based feature attribution, as increasingly applied in the broader crop pest and disease prediction literature, should be a priority for any system intended for practical deployment.

9.5 Edge Deployment for Real-Time Sorting

Mechanized billet-sorting applications require inference at line speed on potentially resource-constrained embedded hardware. Model compression techniques (pruning, quantization, lightweight backbone architectures) proven in other real-time agricultural detection contexts warrant systematic evaluation for this specific application.

9.6 Integration with Robotics for Automated Cutting and Sorting

Closing the loop between automated quality assessment and physical sorting or cutting action for example, a robotic or actuated mechanism that automatically diverts flagged low-quality nodesrepresents a natural extension of a validated detection and classification system, consistent with the broader shift toward closed-loop "detect-decide-act" systems observed in other areas of precision agriculture.

9.7 Climate-Driven Variability and Long-Term Model Robustness

Changing climatic conditions may alter moisture dynamics, pest pressure, and varietal performance over time, potentially degrading the long-term robustness of models trained on historical data. Adaptive or periodically retrained models, informed by ongoing field validation, will likely be necessary to maintain performance as growing conditions evolve.

10. Conclusion, Research Gap, and Contribution

This review has surveyed the sensing technologies, artificial intelligence methods, dataset practices, and deployment contexts relevant to sugarcane stem node quality assessment and bud germination-suitability prediction. Sensing options range from low-cost, readily deployable RGB imaging to higher-cost, higher-information modalities such as hyperspectral and X-ray imaging, each suited to different points along the spectrum from smallholder field use to certified nursery-scale quality assurance. Algorithmic approaches span traditional machine learning, deep learning-based detection and segmentation, transfer-learning and transformer-based classification, and multimodal fusion, with germination-suitability prediction requiring a distinct framing that incorporates post-imaging storage and environmental history.

Across all sections, a consistent finding emerges while individual sensing and algorithmic components have been well validated in analogous crop quality-grading and pest-detection contexts, none have yet been systematically adapted, validated, and integrated for the specific problem of sugarcane stem node quality assessment and bud germination-suitability prediction. In particular, there is not publicly available, diverse, and reliably annotated sugarcane node/bud image dataset; no established consensus on how to reconcile easily obtained proxy quality labels with the delayed, ground-truth germination outcome; and no reported end-to-end intelligent system that combines node detection, quality classification, and germination-suitability prediction within a single evaluated pipeline. This constitutes the specific research gap this review has sought to establish.This gap directly motivates research in this area whose three objectives map directly onto the gaps identified above: **(1)** the collection and annotation of a diverse sugarcane stem node image dataset directly addresses the dataset-scarcity gap identified in Section 6; **(2)** the design and development of an intelligent AI-driven system for node quality assessment and bud germination-suitability classification directly addresses the absence of an integrated, end-to-end system identified across Sections 5 and 8; and **(3)** the systematic analysis of system performance across key classification parameters directly addresses the need, identified in Section 9, for rigorous, reproducible evaluation including interpretability and cross-variety/regional generalization testing that has been largely absent from adjacent areas of agricultural AI research applied to seed and propagation material. In combination, these objectives make a distinct and needed contribution to the intersection of precision agriculture, computer vision, and sugarcane seed-cane quality management.

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