International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

Smart Microwave Sensor-Based Bottle Defect Detection, Filling, and Capping System

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Abstract **-** Bottle-packaging quality depends on several distinct operations, including container inspection, liquid filling, cap application, and verification of the finished package. This review examines selected publications from 2018 to 2026 on microwave non-destructive testing, microwave-based material characterization and level sensing, machine-vision inspection, deep-learning methods, and automated filling and capping. The literature is organized by the task addressed rather than by sensor name alone, because bottle-presence detection, structural-defect identification, material characterization, and liquid-level estimation are not interchangeable functions. The reviewed studies also differ in specimen materials, inspection regions, datasets, operating conditions, and reported metrics; therefore, their numerical results do not support a single cross-method ranking. The review compares these distinctions and identifies the evidence needed to validate microwave sensing on actual bottle materials and to integrate inspection decisions with packaging control. The accompanying project report documents a prototype that uses camera-based silhouette analysis with an ESP32-controlled handling, filling, and capping sequence. It does not establish microwave-based structural-defect detection in the prototype. Open research needs include bottle-specific microwave validation, detection of fine surface defects, feedback-based filling and cap tightening, fault-aware subsystem integration, and reproducible evaluation protocols.

Index Terms **-** automated capping, bottle defect detection, embedded control, machine vision, microwave sensing, nondestructive testing, bottle filling.

I. INTRODUCTION

Bottle packaging is widely used in food, beverage, pharmaceutical, cosmetic, and chemical production. A typical line must identify incoming containers, inspect them, fill them to a specified level, apply caps, and verify that the finished packages meet quality requirements. A defect that is not detected before filling can waste both product and packaging material. Inconsistent filling, poor cap engagement, and unreliable bottle positioning can also reduce product quality and process efficiency.

Automation can coordinate these operations, but the sensing tasks must be defined carefully. A sensor that confirms the presence of a bottle does not necessarily identify a crack or deformation. Similarly, a liquid-level measurement does not establish the structural integrity of the container. Microwave sensing, optical inspection, and embedded control can therefore be complementary, but their roles must be validated separately before they are combined.

A. Review Scope and Approach

This review synthesizes selected publications from 2018 through 2026 concerning microwave material inspection and characterization, liquid-level sensing, machine-vision and deep-learning inspection, and automated filling and capping. The studies are grouped according to their target task and sensing or control method. Numerical results are retained only when they are attributed to a cited publication. The review is not presented as an exhaustive systematic search; its conclusions are limited to the selected studies.

Because the publications use different materials, sample sets, test procedures, and performance measures, they are compared thematically rather than ranked numerically. The objectives are to distinguish the tasks addressed by each method, examine reported contributions and limitations, identify evidence gaps relevant to integrated packaging, and relate those findings to the documented prototype without treating prototype observations as published research results.

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II. LITERATURE SURVEY

A. Microwave Sensing, Material Inspection, and Liquid-Level Measurement

Microwave techniques have been investigated for several measurement purposes, but these purposes should not be conflated. Defect evaluation seeks evidence of discontinuities or damage; material characterization estimates material properties; and liquid-level sensing estimates the amount or state of a liquid in a container.

Sun *et al.* developed an integrated microwave sensor system for evaluating defects in dielectric substrates using electromagnetic responses. Their reported application includes commercial substrate materials, rather than bottle-specific inspection specimens [4]. The work supports the use of microwave responses for non-contact material evaluation, but it does not by itself demonstrate detection of bottle cracks, dents, or cap defects. Kurniawati *et al.* proposed a reflective-mode phase-variation sensor based on a dumbbell defect-ground-structure resonator. Changes in the reflection phase are used to characterize solid and liquid samples [5]. This is a material-characterization contribution; transferring it to bottle inspection would require a defined bottle geometry, material reference, and defect-specific experiment.

Li *et al.* combined a Bluetooth Low Energy planar inverted-F antenna sensor with machine learning for non-contact liquid-level and volume estimation. The reported random-forest configuration achieved an R^2 value of 0.9885 for volume prediction [6]. This result is relevant to liquid monitoring, not structural-defect detection. In a different specimen domain, Xiao *et al.* used microwave non-destructive-testing data and imaging methods to identify butt-fusion defects in polyethylene pipes [8]. Ghattas *et al.* reviewed microwave non-destructive testing approaches for material-defect detection across application areas [9]. These works establish technical context for microwave inspection, but neither pipe-joint imaging nor a general review is direct evidence of performance on glass or plastic bottles.

Taken together, these studies suggest opportunities for microwave measurements in packaging, while leaving application-specific validation unresolved. A bottle experiment must control for wall material and thickness, bottle geometry, liquid properties, sensor placement and orientation, and the defect classes of interest. The target output must also be specified: material-property estimation, liquid-level estimation, presence detection, and structural-defect classification require different references and validation criteria.

B. Machine Vision for Bottle and Cap Inspection

Machine-vision systems inspect visible features, and their performance depends on the surface being viewed, illumination, camera geometry, and the defect types represented during development and testing. Zhou *et al.* presented a saliency-detection and template-matching method for glass-bottle-bottom inspection [1]. Their later framework combined visual attention and wavelet transformation for surface-defect detection on glass-bottle bottoms [2]. The two studies address the same bottle region using different image-analysis strategies. Their results should not be extrapolated to sidewalls or caps without additional views and representative test samples.

For cap inspection, He *et al.* proposed a high-angle, multi-view vision system that images the outer surface of a bottle cap from four views. The study reports inspection accuracy above 95% and speed above 400 pieces per minute for its evaluated configuration; weak defects and irregular edge features are identified as challenging cases [3]. These limitations illustrate why illumination design and complete surface coverage matter as much as the selected detection algorithm. Ismail *et al.* evaluated a camera-based inspection system for plastic perfume bottles using image thresholding and automated sorting. The publication reports accuracy above 95% for the tested batches, but that result remains tied to its particular threshold, bottle type, and batch-level evaluation [10].

The vision studies therefore differ in both target region and inspection arrangement. Bottle-bottom methods, multi-view cap inspection, and perfume-bottle sorting do not form a directly comparable set unless they are evaluated on common defect definitions and documented sample conditions. A production system must specify the surfaces inspected, camera and lighting arrangement, acceptable variation, and the costs of false acceptance and false rejection.

C. Deep-Learning Methods for Visual Inspection

Learned image models are used for tasks ranging from fill-level classification to surface-defect detection. Dhama *et al.* described a convolutional-neural-network approach using MobileNetV2 for automated bottle fill-level detection [11]. Its target is the state of the fill, not the physical integrity of the container. Consequently, its evaluation should be interpreted in terms of fill-level categories and the dataset and conditions used for that task.

Han *et al.* proposed HP-YOLO11n for surface-defect detection on liquor-bottle caps. The paper reports an mAP@0.5 of 87.06% and a 44.57% reduction in model parameters relative to its comparison model [12]. The reported parameter reduction indicates a smaller model, but it does not alone establish real-time performance on a particular embedded processor. Inference latency, memory use, power consumption, and performance on unseen caps remain relevant deployment measures.

Classical image processing can be appropriate when the target defect has a stable geometric signature and the imaging arrangement is controlled. Learned models may be preferable when the defect appearance varies or includes texture and surface information that cannot be represented by a silhouette. A meaningful comparison should use common images and labels and report precision, recall, missed-defect rate, false-reject rate, processing time, and computing requirements.

D. Automated Filling, Capping, and Packaging Control

Packaging automation combines sensing, mechanical positioning, actuators, and sequential control. Pandey *et al.* described a bottle-filling and capping plant using a Raspberry Pi, Arduino Uno, sensors, and conveyor automation. The study

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reports 97% fill-level detection accuracy and a 30% reduction in total production time under its test conditions [7]. These results concern the reported plant and its baseline; they should not be interpreted as a general performance guarantee for other lines.

Albin described a filling system controlled by a DELTA DVP14SS2 programmable logic controller. Photoelectric sensors, a conveyor, a relay-controlled pump, and ladder-logic control coordinate the filling operation [13]. This work illustrates how sensor inputs can be linked to actuators in a PLC architecture, but its described focus is filling control rather than validated bottle-defect inspection or cap-quality measurement. Compared with microcontroller-based arrangements, the PLC example uses a different control platform; controller type alone does not establish relative cost, reliability, or throughput.

At the system level, the reviewed work does not provide a common set of measurements for defect rejection, fill variation, closure quality, response time, fault recovery, and production throughput. These measures are needed to assess whether sensing and actuation functions operate reliably as one process.

III. COMPARATIVE ANALYSIS

Table I summarizes the principal tasks, contributions, and evidence limitations of the reviewed studies. The comparison shows that the literature covers distinct stages of a packaging process rather than interchangeable solutions to one inspection problem.

First, vision methods are generally designed around a particular surface or defect class. The glass-bottle-bottom studies [1], [2], the outer-cap inspection system [3], and the perfume-bottle inspection method [10] differ in geometry, imaging arrangement, and target features. Second, microwave studies cover substrate-defect evaluation, solid/liquid characterization, liquid-volume estimation, and pipe-joint inspection [4]–[6], [8], [9]. They provide related sensing principles, but they do not constitute a single validated microwave solution for bottle defects. Third, the filling and capping studies use different control architectures and do not report a consistent set of quality and throughput measures [7], [13].

The reported values also measure different outcomes. Classification or detection accuracy, mAP@0.5, a regression coefficient of determination, parameter reduction, and production-time reduction cannot be placed on a common scale. For each result, an interpretable comparison requires the target variable, specimen type, sample count, baseline, operating conditions, and evaluation procedure. In particular, model size is not a substitute for inference latency, and a high liquid-volume prediction coefficient is not evidence of structural-defect detection.

A. Relation to the Developed Prototype

The supplementary project report describes a low-cost prototype that combines camera-based inspection with embedded handling, filling, and capping. An ESP32 executes a sequential control program. A USB camera views the bottle against a controlled white backlight and hood; a separate computer processes the image using Python and OpenCV. The documented inspection sequence converts the frame to grayscale, applies thresholding, extracts the outer contour, and compares the contour with a reference bottle using Hu-moment shape matching and a bounding-box size check. The report lists a shape-distance rejection threshold of 0.05 and a size tolerance of approximately ±16%. The inspection result is returned to the ESP32 over a USB serial link; the firmware treats a missing result within the specified timeout as a rejection.

Accepted bottles are held by a servo-operated gripper on a stepper-driven M8 lead-screw carriage and transferred through the filling, capping, and unloading positions without releasing the bottle between stations. The report specifies two 8-mm guide rods, limit switches for homing and travel protection, a pump operated for a preset filling interval, and a motor-driven capping mechanism. A four-channel relay module switches the pump, capping motor, input conveyor, and reject pusher. The mechanical design was modelled in FreeCAD and fabricated using MDF panels and 3-D-printed parts. The documented operating configuration is for a single bottle size and water as the test liquid.

The project report contains one inconsistency relevant to the paper title: its block-diagram description names an RCWL-0510 microwave sensor for bottle presence at the camera station, whereas its detailed pin assignment and hardware-component table specify an IR sensor at the inspection trigger and list three IR modules. The report does not provide a separate microwave measurement or microwave-based structural-defect result. Accordingly, the documented defect-inspection method in the prototype is optical silhouette analysis; the report does not substantiate a claim that microwave sensing performs the defect classification.

The report records a cycle time of approximately 1.5 min per bottle, 90% capping success over 20 bottles, 90% bottle-detection reliability over 50 bottles, and 90% defect-detection accuracy over 20 good and 20 damaged bottles. It also records 100% fill-volume accuracy, but does not provide the corresponding mean, standard deviation, or acceptance tolerance in the results table. These values are project-reported prototype observations, not results from the publications reviewed above. Their sample sizes and incomplete reporting mean that they should not be used as direct benchmarks against the published systems.

The prototype illustrates a practical integration strategy: reject visibly deformed bottles before filling, then retain a consistent bottle reference through subsequent stations. Its silhouette-based method is inexpensive and does not require a labelled training dataset, but it cannot detect surface cracks, scratches, or label defects that do not change the bottle outline. The report also identifies time-based filling and capping, no torque feedback, manual cap placement, single-bottle throughput, and one bottle size as limitations. These constraints connect the prototype to the broader research needs for complementary sensing and closed-loop packaging control.

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TABLE I
COMPARISON OF REVIEWED STUDIES

Ref.	Method / application	Reported result or contribution	Limitation or evidence gap
[1], [2]	Saliency/template matching and visual-attention/wavelet methods for glass-bottle-bottom inspection	Two image-analysis approaches for automated surface-defect inspection of glass-bottle bottoms [1], [2]	Both target the bottle bottom; coverage of the body or cap is not established. Direct comparison needs matched test conditions.
[3]	High-angle, four-view vision for the outer surface of bottle caps	Accuracy above 95% and inspection speed above 400 pieces/min in the reported setup [3]	Weak defects and irregular edge features remain difficult; results depend on the illumination and viewing geometry.
[10]	Machine-vision inspection and sorting of plastic perfume bottles	Threshold-based USB-camera inspection; accuracy above 95% is reported for tested batches [10]	The result is specific to the tested material, threshold, batch composition, and evaluation procedure.
[4]	Integrated microwave sensor for dielectric-substrate defect evaluation	Electromagnetic responses are used to evaluate defects in substrate materials [4]	Substrate testing does not establish sensitivity to cracks or dents in bottle materials.
[8]	Microwave NDT imaging for polyethylene pipe butt-fusion defects	Microwave data are processed to form images for pipe-joint defect inspection [8]	Pipe-joint inspection is not direct evidence of bottle-defect detection performance.
[9]	Review of microwave NDT for material defects	Summarizes microwave NDT methods and their material-inspection context [9]	A general review does not provide experimental validation on bottles.
[5]	Reflective-mode DB-DGS microwave resonator for solid and liquid characterization	Uses phase-response variation to characterize samples [5]	Material characterization is distinct from structural-defect detection on bottles.
[6]	BLE PIFA microwave sensor with machine learning for IoT liquid-level sensing	Random-forest volume prediction with reported $R^2 = 0.9885$ in the evaluated configuration [6]	Predicts liquid volume; it does not establish structural-defect inspection or complete packaging control.
[11]	CNN and MobileNetV2 for bottle fill-level detection	Applies deep learning to automated visual fill-level detection [11]	Dataset composition and test conditions must be considered before production-line comparison.
[7]	Raspberry Pi, Arduino Uno, machine vision, sensors, conveyor, filling, and capping	Reports 97% fill-level detection accuracy and 30% lower production time under its test conditions [7]	Baseline and operating conditions are specific to the reported plant; this is not equivalent to structural-defect validation.
[12]	HP-YOLO11n for liquor-bottle-cap surface defects	Reports mAP@0.5 of 87.06% and 44.57% fewer model parameters [12]	mAP@0.5 is not classification accuracy; deployment speed requires hardware testing.
[13]	DELTA DVP14SS2 PLC-controlled bottle filling	Describes ladder-logic filling with photoelectric sensors, a conveyor, and a relay-controlled pump [13]	The described focus is filling; the paper does not establish bottle-defect inspection or cap-quality verification.

IV. CHALLENGES AND RESEARCH GAPS

A. Presence Detection Versus Defect Identification

Presence sensors determine whether an object is at a location; they do not, by themselves, classify damage. The reviewed optical and microwave studies have different target outputs, and each requires a task-specific reference and validation protocol. Future integrated systems should expose separate decisions for bottle presence, structural condition, liquid level, and cap condition rather than treating them as one generic sensor result.

B. Application-Specific Microwave Validation

Microwave non-destructive testing has been demonstrated for substrate and pipe applications, while microwave characterization and antenna-based sensing have been used for solid/liquid properties and liquid-level estimation [4]–[6], [8], [9]. The selected literature does not directly establish microwave defect detection on the glass and plastic bottles considered in packaging. Experiments are needed across bottle materials, wall thicknesses, liquid contents, defect classes, sensor distances, and orientations. The distinction between a microwave presence trigger and a microwave structural-defect measurement must remain explicit.

C. Inconsistent Metrics and Test Conditions

The reviewed papers report accuracy, mAP@0.5, R^2, parameter reduction, and production-time reduction. These metrics describe different outcomes and cannot be compared directly. Some reports provide limited information about sample counts, defect severity, illumination, data splits, repeatability, or baselines. A stronger evaluation should state the specimen population, defect taxonomy, train/test separation where learning is used, lighting and sensor geometry, false-acceptance and false-rejection rates, processing latency, and computing platform.

D. Inspection and Packaging Integration

An integrated line must coordinate bottle positioning, inspection decisions, pump control, cap placement, and rejection. However, the reviewed system-level studies do not consistently report defect-rejection performance, fill-volume variation, closure quality, response time, fault recovery, throughput, and equipment cost together. A failed camera response, invalid sensor reading, bottle jam, or cap-feed interruption should produce a defined safe response before the bottle advances. The project prototype provides an example of timeout-based rejection and limit-switch protection, but broader repeatability and fault-injection testing would be needed to establish production reliability.

E. Project-Specific Limitations and Evidence Gaps

The supplied project report identifies several gaps in the developed prototype: its contour-based inspection is limited to silhouette-changing defects; filling is controlled by time rather than measured volume; capping has no torque feedback; caps are placed manually; and one carriage processes one bottle at a time. The report also describes a single bottle geometry and water as the test liquid. The reported performance table does not provide all underlying measurements needed to reproduce each

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

metric. These limitations are specific to the project prototype and should not be generalized to all packaging systems.

V. FUTURE SCOPE

A. Complementary Sensing and Microwave Experiments

Future work should evaluate microwave sensing for a clearly defined bottle-related task, such as material characterization or liquid-level estimation, before testing it as a structural-defect detector. Tests should control bottle material, wall thickness, contents, sensor orientation, distance, and temperature. Optical inspection should be evaluated separately, with distinct outputs and acceptance criteria.

B. Improved Visual Inspection

The prototype's silhouette method can be extended with additional camera views and controlled illumination to inspect regions not represented by a single side outline. Fine cracks, scratches, label defects, and cap-surface defects require image information beyond the external silhouette. A labelled dataset may support a learned detector; split it by bottle or batch to prevent near-duplicate images crossing training and test sets. Evaluation should report precision, recall, false accepts, false rejects, latency, and hardware requirements.

C. Feedback-Based Filling and Capping

A flow sensor or load cell could supplement time-based filling and measure volume directly despite pump-flow changes. Repeated-cycle tests should report the mean fill volume, standard deviation, and deviation from the target. Cap tightening could use torque feedback, motor-current monitoring, or a calibrated slip mechanism. Closure quality should be measured independently of motor run time.

D. Throughput, Monitoring, and Validation

A higher-lead screw or belt drive, multiple grippers, parallel stations, and automatic cap feeding could be investigated to increase throughput. Monitoring could record bottle counts, rejected bottles, fill measurements, capping outcomes, and machine faults. A reproducible validation plan should define bottle type, sample size, operating conditions, defect severity, baseline, cycle count, and metric calculations. Report inspection quality, fill consistency, closure quality, throughput, fault recovery, energy use, and cost where applicable.

VI. CONCLUSION

This review examined selected work on microwave sensing, machine vision, deep-learning inspection, and automated filling and capping. The publications address distinct tasks: glass-bottle-bottom and cap inspection, material-defect evaluation, material characterization, liquid-level prediction, and packaging control. Their results must be interpreted in relation to their specimens, sensing arrangements, datasets, and evaluation metrics; they do not support a single ranking across all methods. The supplementary project report documents a low-cost bottle-processing prototype using camera-based silhouette inspection and an ESP32-controlled sequence for handling, filling, capping, and unloading. It provides an implementation context for integrating early rejection with packaging operations, but it does not demonstrate microwave-based structural-defect classification. The report's conflicting descriptions of the inspection-trigger sensor and limited prototype tests should be resolved in a subsequent version. Further work should validate microwave methods on actual bottle materials, improve detection of non-silhouette defects, introduce feedback for filling and cap tightening, and evaluate throughput and fault handling under repeatable conditions. An integrated system will require task-specific sensor validation and shared system-level performance measures.

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