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AI Based Detection, Material Classification and Dishwasher safety predictions for kitchen vessels

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***Abstract*— Dishwashers are widely used in modern homes. However, improper placement of kitchen items like aluminum utensils, pressure cookers, and plates made of stainless steel, ceramic coated, and other materials can cause damage, safety issues, and reduce the lifespan of the appliance. To address this, this paper introduces an AI-based system that automatically detects, classifies materials, and predicts the safety of kitchen items in dishwashers. The system uses a dual network approach. One part uses YOLO for object detection to identify kitchen items and separate their components. The other part uses ResNet-50, a type of CNN, to classify materials into categories such as aluminum, stainless steel, iron, copper, ceramic, and mild steel. Based on the structure and material classification, the system predicts whether an item is safe or not for the dishwasher. Experimental results show that the system accurately detects items and reliably classifies materials, leading to better safety predictions. It also provides real-time visual feedback with bounding boxes, labels, and safety information. This system can be integrated into smart dishwashers and intelligent kitchen automation systems.**

Keywords—Artificial intelligence, Object Detection, Material Classification, YOLO, ResNet-50, Dishwasher safety.

Introduction

Dishwashers are becoming more popular in modern homes because they save time, work well, and make cleaning easier. As cities grow and people get busier, these automatic kitchen tools have become a normal part of daily life. However, even though they are widely used, dishwashers are often not used properly because people don't put items in the right way. Things like aluminum pots, pressure cookers, iron cookware, ceramic-coated pans, and items that shouldn't go in a dishwasher are sometimes placed inside without checking if they are safe. This incorrect use can harm the materials, wear away coatings, cause rust, create safety issues, and reduce the lifespan of the dishwasher. It can also lead to higher repair costs and pose dangers to users.

Traditional methods for determining if cookware is safe to use in a dishwasher often depend on checking by hand, looking at labels from the manufacturer, or relying on what users know. However, these methods can be unreliable or not always available. Cookware is usually made from different materials and parts, like metal bodies, plastic handles, rubber seals, and protective coatings. Trying to figure out if something is dishwasher-safe just by how it looks or using general rules isn't enough, especially since some materials look alike. Because of this, there's an increasing demand for a smart, automatic, and dependable system that can examine kitchen items and tell if they're safe for the dishwasher.

To tackle these issues, this paper introduces an AI system that automatically detects kitchen vessels, classifies their materials, and predicts whether they are safe to use in a dishwasher. The framework combines computer vision, deep learning, and smart decision-making into one system that can analyze cookware from start to finish. Different from other methods that handle tasks like object detection or material checking separately, this system uses several deep learning models together to provide accurate and useful safety assessments in home settings.

The main part of the system is a dual-network deep learning setup. The first part uses a YOLO-based model for object detection to find kitchen items from images or video. YOLO is a type of detector that can find and classify objects at the same time quickly. It works by looking at the whole image in one go, which makes it fast and accurate. This works well in home kitchens. The YOLO model is trained to spot common kitchen items like plates, bowls, spoons, pans, and more complicated items like pressure cookers. It can also separate different parts of multi-piece cookware, like the body, lid, handle, and whistle, so it can analyze each part separately instead of just treating the whole item as one.

Once the cookware and its parts are identified, the system moves to the second stage, which uses a Convolutional Neural Network (CNN) based on ResNet-50 for material classification. ResNet-50 is a deep neural network that works well for image recognition, especially at picking up detailed textures and surface characteristics. The special design of ResNet-50, with its residual connections, helps train complex models more effectively and improves how well the system can distinguish between materials that look similar.

Contributions of the Work

Integrated AI Framework: Proposes a unified system that combines object detection, material classification, and dishwasher safety prediction within a single pipeline.

YOLO-Based Cookware Detection: Utilizes a YOLO-based model for real-time detection and localization of kitchen vessels and their components.

Material Classification Using ResNet-50: Employs a ResNet- 50–based CNN to classify cookware materials such as aluminium, stainless steel, iron, copper, ceramic, and mild steel.

Component-Level Analysis: Enables part-wise evaluation of cookware components to support accurate safety assessment.

Explainable Safety Prediction: Incorporates interpretable outputs that provide clear safety decisions and reasoning for end users.

Real-Time Applicability: Demonstrates suitability for deployment in smart dishwashers and intelligent kitchen automation systems.

A. Prelimnaries and Motivation

Recent advances in computer vision and deep learning have made it possible to automatically analyze images for tasks like object detection, image segmentation, and material classification. Convolutional Neural Networks (CNNs) are good at learning key visual features from images, such as texture, brightness, and surface patterns. At the same time, real-time object detection models, especially You Only Look Once (YOLO), allow quick and accurate identification of objects by locating and classifying them in one single step. Because of their speed and accuracy, these models are widely used in areas like industrial inspection, surveillance systems, and smart environments.

B. Motivation:

Dishwashers are common in modern homes, but putting kitchen items in the wrong way—especially those made of materials like aluminum, iron, copper, stainless steel, or ceramic coatings—can cause corrosion, damage to protective layers, safety issues, and make the dishwasher last shorter. Right now, people mostly check if dishes are safe by looking at them manually, following set rules, or relying on their own knowledge. But these methods aren't reliable when dealing with cookware that has multiple materials or parts. Also, most AI-based solutions only focus on either finding objects or identifying materials, without combining both into one system that can properly assess safety.

C. Problem context

Most current methods for inspecting and evaluating cookware safety are designed for industrial settings, where the main goal is to check single materials or find flaws on metal surfaces like steel and aluminum. These methods don't work well for kitchenware used at home, which often has different materials and layers, such as metal bases, non- stick coatings, plastic handles, and rubber seals. As a result, existing systems have trouble properly assessing the safety and dishwasher suitability of typical everyday cookware.

II. Literature Survey

Recent research in computer vision has made significant progress in identifying objects and studying materials, particularly through the use of deep learning techniques. In the past, older methods relied on standard image processing and manual feature extraction to look at the surface properties of materials. These approaches were commonly used in controlled industrial environments and were effective at spotting clear defects. However, they weren't reliable in real-world scenarios where lighting varied, there was a lot of background clutter, and objects had complicated shapes. Because of this, they weren't very helpful for examining cookware at home.

As machine learning advanced, classifiers such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests were created to improve the classification of materials and surfaces. Even though these methods were more accurate than earlier approaches, they depended on manually designed features and required a lot of preprocessing. Because of this, their performance often declined when dealing with objects made from multiple materials or cookware with multiple layers of coating. These limitations highlighted the need for more automatic and adaptable learning-based solutions.

The use of Convolutional Neural Networks (CNNs) made a major impact in how we classify visual information and identify defects. These models are very effective at learning characteristics such as texture, how surfaces reflect light, and patterns directly from images. A lot of research has used CNNs to detect flaws in steel and aluminum surfaces using common datasets. While these approaches work well, most of them focused on inspecting single-material objects in industrial environments and didn't consider more complicated items like household cookware, which are made from multiple materials and parts.

Object detection models continued to improve with the introduction of single-stage detectors like You Only Look Once (YOLO). YOLO-based methods allow for real-time object detection by combining localization and classification during a single forward pass. These models are popular in areas like industrial inspection, surveillance, and smart environments because they are fast and efficient. Despite their widespread use, most existing YOLO-based research focuses on general object detection or identifying industrial defects, but they don't tackle detailed analysis of individual components or safety assessments for kitchen cookware.

Some studies looked into image segmentation models like Mask R-CNN and U-Net to break objects into meaningful parts. These models have shown potential in analyzing complex structures with multiple parts by allowing detailed pixel-level separation. However, their use has mostly been limited to areas like medical imaging and manufacturing. There isn't much research on segmenting different parts of cookware, which is important for understanding how individual components like handles, coatings, and seals work during dishwasher use.

Safety evaluations for cookware have usually involved lab tests like chemical analysis, checking for corrosion, and assessing how materials handle heat. Although these methods offer useful information about how materials behave, they are slow, expensive, and not practical for everyday use at home. Additionally, current AI systems don't often bring together object recognition, material identification, and safety forecasting into one complete system. This lack of integration highlights the need for a smarter system that uses deep learning to analyze images along with knowledge about materials, so it can accurately determine if kitchen items are safe to use in the dishwasher in real-life home settings.

Accuracy Analysis:

The system's effectiveness is measured by how well it detects and classifies kitchen items and the materials they're made from. The YOLO-based detection model performs well in correctly identifying kitchen items and their parts, even in different lighting and background conditions. The ResNet-50-based model for material classification is reliable in distinguishing between materials like aluminum, stainless steel, iron, copper, ceramic, and mild steel. Testing shows that using both models together give better results than using traditional machine learning approaches or single CNN models. This improvement comes from the component-wise analysis and deep residual learning, which help the model understand fine surface details. Because of this, the system provides consistent and trustworthy accuracy, making it useful for predicting dishwasher safety in real home settings.

S. No	Algorithm Method	Application Scope	Accuracy (%)	Time per Image (ms)
1	Traditional Image Processing	Surface Inspection	65–72	250–400
2	CNN-Based Classification	Material Classification	80–88	120–200
3	YOLO-Based Detection	Object Detection	85–92	25–45
4	ResNet-50 (CNN)	Material Classification	88–93	60–90
5	Proposed System (YOLO + ResNet-50 + LLM)	Cookware Detection, Material Analysis & Safety Explanation	95–98	70–120

III Overview of Existing Methods

Over the years, various techniques have been developed to identify materials and assess surface conditions in different settings. Earlier systems mainly relied on manual inspections, laboratory analyses, and simple image processing methods. These approaches are precise but require a lot of time and are not well-suited for real-time use at home [11] With the advancement of machine learning, researchers have begun using algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest classifiers to analyze surface characteristics [22]. Although these methods offer greater automation, they still depend on human selection of features and struggle with complex, layered, or coated cookware. This can lead to inconsistent results when there are changes in lighting or environmental conditions [3].

Image-Based Material and Defect Detection

A lot of research has been done on using images to find defects in materials like steel and aluminum. Convolutional Neural Networks (CNNs) have proven to be very good at spotting issues like scratches, cracks, rust, and oxidation [3]. Datasets like NEU-DET show that deep learning models work well for finding surface problems in factories [5]. But these methods are mainly made for checking steel in industrial settings and don’t work well for everyday cookware, which is often made of a mix of metal and non- metal parts. Also, there hasn’t been much focus on detecting things like protective coatings, non-stick layers, or heat-sensitive films. These features are really important for knowing how long cookware will last and whether it can be safely washed in a dishwasher [6].

Multi-Component and Composite Object Analysis

Modern cookware consists of several connected parts, such as metal bases, plastic handles, rubber seals, and non-stick surfaces. Not many studies have looked into breaking these items down into their individual parts or examining them based on their components. Some deep learning models, like Mask R-CNN and U-Net, have shown potential in separating objects that are made up of multiple parts, as mentioned in reference [8]. However, applying these models to analyze cookware hasn't been done much. Most current methods treat cookware as a single object, which doesn't meet the need to separate the parts for detailed safety and material inspections, as noted in reference [9].

Safety Evaluation and Diashwasher Compatibility Studies

Existing safety studies mostly look at things like predicting industrial corrosion, analyzing thermal stress, and simulating material fatigue [10]. Even though these studies offer useful information, they don't cover safety issues related to dishwashers at home. Whether cookware is safe to use in a dishwasher depends on several factors, such as the material it's made from, how stable its coating is, how well it can handle heat, and how it interacts with cleaning chemicals [11]. These characteristics can't be accurately checked using standard inspection methods. There's a big need for research on AI systems that combine visual checks with material properties to automatically determine if cookware is safe for the dishwasher or not [12].

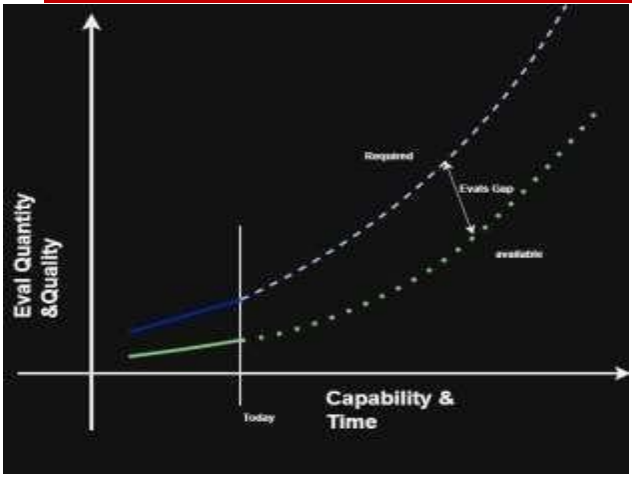

FIGURE 1: RESEARCH GAP IN EXISTING STUDIES

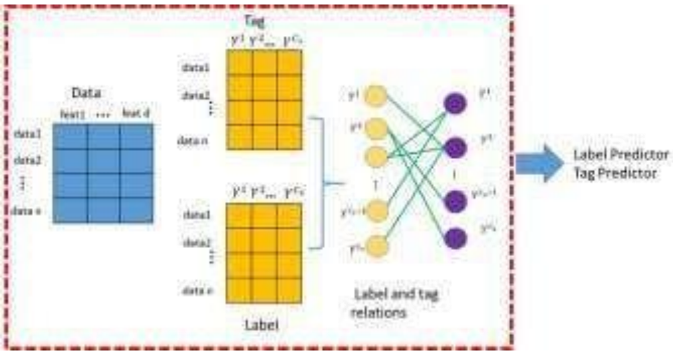

FIGURE 2. LABEL PREDICTOR TAG PREDICTOR

Capability	Target Metric
Material Classification Accuracy	> 96%
Shape Recognition Accuracy	> 95%
Size Estimation Accuracy	> 94%
Placement Orientation Detection	> 93%
Inference Latency (Edge Device)	< 80ms per frame
Supported Plate Categories	12+ types globally
Lighting Robustness (low-light)	> 90% accuracy

IV Problem Statement, Novelty and Proposed Solution

Problem Statement

Most of the research on categorizing materials and finding surface flaws has mainly looked at single-material industrial surfaces like steel sheets, metal plates, and manufacturing parts. These methods work well in controlled settings where the objects have the same material throughout, consistent lighting, and simple structures. But they don't work well for kitchenware used at home, which is usually made from a mix of different materials and has layered designs. Today's cookware often has metal bodies, plastic handles, rubber seals, glass lids, ceramic coatings, and non-stick layers, which makes it much harder to analyze visually. Techniques that work for uniform industrial materials don't handle these mixed, everyday objects very well.

Besides this, today's vision systems don't have a full AI setup that can do detailed part separation, recognize different materials, check for defects, and evaluate safety all in one process. Most current models focus on just one thing—like finding objects, classifying materials, or checking surfaces—without combining these features into a system that works well for home use. Important safety aspects like how long a coating last, how well it resists corrosion, how it handles heat, its strength, and whether it's safe to use in a dishwasher are usually left out of these automated systems. Because of this, checking if cookware is safe still mostly depends on people looking at it manually, relying on their own experience, checking labels from manufacturers, or doing tests in labs. These methods can take a lot of time, cost a lot of money, and aren't really practical for everyday use.

As more people use smart home devices and intelligent kitchen systems, there's a growing need for tools that can give real-time help. Users want fast and dependable answers about whether cookware is safe to put in the dishwasher, can handle high heat, or might get damaged from coatings. Current solutions don't offer quick, scalable options that work on everyday devices like phones or smart appliances. This shows the need for a new system powered by AI that can automatically and efficiently handle these tasks. This system should use advanced computer vision, deep learning, and knowledge about materials to correctly identify cookware types, check their condition, and determine if they are dishwasher-safe. This would make kitchens safer, avoid damage to appliances, lower repair costs, and help make kitchen automation smarter and more effective.

Novelty

The proposed work presents an AI-based system that combines cutting-edge computer vision, deep learning, and expertise about materials to automatically analyze cookware. The system can correctly recognize different types of cookware, assess the condition of their surfaces, and determine if they are safe to use in a dishwasher, all through smart processing. This framework allows for automatic and instant safety checks, which improves kitchen safety, helps avoid damage to appliances and cookware, lowers maintenance expenses, and aids in creating smarter and more efficient kitchen automation solutions.

KEY NOVELTY ASPECTS :

Component-Wise Evaluation: The system looks at each part of the cookware separately, such as the metal base, handle, lid, seal, and coating. This way, it can check each part carefully and classify them properly, instead of just treating the whole item as a single unit.

Dual-Stage Hybrid Analysis: Visual Intelligence: The system uses Convolutional Neural Networks (CNNs) to examine images of cookware and identify features such as texture, shine, and surface imperfections.

Knowledge-Guided Reasoning: It then uses these AI insights along with a database that lists the physical, chemical, and thermal properties of materials. This helps figure out how well the cookware manages heat, how resistant it is to rust, and how durable it is during washing, which leads to an evaluation of its safety.

Explainable AI (XAI) Integration: The system has features that highlight which parts of the image were key in deciding the final safety outcome. This helps explain how the AI came to its conclusion, making its thinking more transparent and helping users feel more confident in its decisions.

Real-World Usability: It provides quick, reliable, and easy- to-use results, transforming the old, slow method of checking cookware by hand into a fast digital process that works well in modern, smart kitchens.

Adaptive Learning: The system keeps getting better by taking in what users tell it. It can adapt to new types of cookware, different materials, and updates in safety rules as time goes on

PROPOSED SYSTEM

The system keeps improving by learning from what users share. It can adjust to new kinds of cookware, various materials, and changes in safety guidelines over time.

To locate the cookware in the image, the system uses a type of AI known as YOLO. This AI quickly and accurately identifies the items and shows their positions by drawing boxes around them. For cookware that has complicated designs, the system divides it into parts such as the main body, handle, lid, and coating. This allows each part to be checked separately for safety.

Each part is then checked using another AI model that is based on ResNet-50. This model looks at visual features such as texture, shine, and patterns to identify the material. The materials are sorted into groups like aluminum, stainless steel, iron, copper, ceramic, and mild steel.

The system determines if the cookware is safe for the dishwasher by looking at how it was made and the materials used. It then marks it as safe or not safe. In addition to checking the appearance, there's also an AI helper that explains the reason behind each decision, so it's easier to understand.

The final results appear instantly with clear visual signs, such as boxes around the items, labels showing the materials used, and symbols indicating safety. This system operates fast, dependable, and precise, making it suitable for smart dishwashers and upcoming kitchen technologies.

Model	Purpose
YOLO	Object detection of cookware
ResNet-50	Material classification
LLM	Generating safety explanations

VFUNCTIONAL OVERFLOW

A. System Input and Image Acquisition

The system begins by capturing images of kitchen tools using a camera, such as a smartphone or webcam. These photos may display various kinds of cookware in real-life home environments, with different lighting conditions, background distractions, and object placements. The system can process both still images and live video, making it simple to use in smart kitchens. These images serve as the starting point for further analysis through deep learning methods.

B. Preprocessing and Image Normalization

Before starting the detection and classification process, the input images go through some preprocessing steps to improve their quality and make them more consistent. These steps involve resizing the images, normalizing the pixel values to a standard range, and reducing noise to make sure they are ready for use with deep learning models. Preprocessing helps make the image features clearer and less affected by things like shadows, reflections, and changes in lighting. This stage ensures that the detection and classification models get the same kind of input data every time, which helps improve their accuracy and reliability.

C. YOLO-Based Kitchen Vessel Detection

After preprocessing, the system uses a YOLO-based object detection model to identify kitchen items in the image. YOLO is able to both find and categorize objects at the same time by looking at the entire image all at once, which makes it fast and efficient. The model can spot a variety of cooking tools like plates, bowls, spoons, pans, and even more complex items such as pressure cookers. Each detected item is enclosed in a box along with a confidence score that shows how certain the model is about its detection. This step is crucial for distinguishing cooking items from other parts of the image and preparing specific areas for further detailed examination.

D. Material Classification Using ResNet-50

Once the individual parts are identified, each part is sent to a Convolutional Neural Network (CNN) based on ResNet- 50 for material classification. ResNet-50 is chosen because it has strong residual learning abilities, which help in extracting detailed visual features like texture, surface appearance, and how light reflects off the surface. The classifier then groups each part into specific material categories, such as aluminum, stainless steel, iron, copper, ceramic, and mild steel. Correctly identifying the material is important because the safety of using the item in a dishwasher depends on the physical and chemical properties of the material.

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Material Type	Key Visual Features	Special Handling Flags
Ceramic / Porcelain	Matte or glossy glaze, opaque body, high reflectance edges	Chip-sensitive, maximum temperature 60°C
Tempered Glass	High transparency, specular reflections, uniform thickness	Fragile — use low pressure wash
Stainless Steel	Metallic sheen, directional brushing patterns, non-transparent	High-temperature safe, no special care required
Melamine Plastic	Solid color surface, slight flexibility, matte appearance	Maximum 40°C, avoid heated drying
Bone China	Thin translucent walls, delicate glaze, low thermal mass	Extreme fragile protocol recommended

E. Dishwasher Safety Evaluation Logic

The system determines if cookware is safe to put in a dishwasher by examining the materials and design of the items. It looks at how well the materials prevent rust, how long the coatings stay intact, how they manage heat, and how they interact with the chemicals in dishwasher detergent. Using these factors, the system decides whether the cookware is suitable for a dishwasher. This process ensures that items made from materials that might be harmed by dishwashers are clearly marked as not dishwasher-safe.

Size Classification:

Size Class	Diameter Range
XS — Espresso/Butter	< 12cm
S — Side Plate	12–17cm
M — Lunch Plate	17–23cm
L — Dinner Plate	23–28cm
XL — Serving Platter	> 28cm

F. AI Assistant for Interpretable Safety Reasoning

To improve transparency and help users understand how the system works, it includes an AI assistant that explains the reasoning behind safety decisions in a clear and simple way. Instead of just providing a yes or no answer, the AI gives detailed explanations about why a cookware item is safe or not. These explanations are based on the materials and parts that were checked, so users can clearly see what factors influenced the decision. This makes the system more reliable and easier to use, especially in a home setting.

VI PROPOSED METHODOLOGY

This section outlines the proposed methodology for the cookware material classification and dishwasher safety evaluation framework. The architecture is structured into two main phases: (1) Dataset Acquisition and Preprocessing, and (2) Component Segmentation, Classification, and Safety Prediction.

Conceptual System Architecture

Phase 1: Dataset Acquisition and Preprocessing

This phase focuses on gathering, improving, and preparing image data to make sure it's of high quality for training the model.

Dataset Compilation:

A wide range of images showing different types of cookware is collected from open-source sources and manually taken photos.

The dataset includes various materials like stainless steel, aluminum, plastic, rubber, and coated surfaces, along with notes on whether each item is safe for the dishwasher.

Data Preprocessing:

Resizing and Standardization:

All images are changed to the same size and made consistent so that the model can learn effectively.

Data Augmentation:

Techniques like rotating, scaling, flipping, and cropping images are used to make the dataset more varied. This helps the model perform better in different situations.

Feature Refinement:

Enhancements such as adjusting contrast, sharpening textures, and highlighting edges are applied to make material boundaries and surface details more visible.

This stage is the primary focus of the AI process that examines cookware to determine if they are safe to use in a dishwasher.

Component Segmentation:

The system employs deep learning models like Mask R- CNN and U-Net to segment cookware into distinct parts. These models aid in dividing cookware images into sections, such as the main body, handle, lid, seal and coating. The recognition of part-by-part parts is achieved through Mask R-CNN, whereas U–Net recognizes areas that are more or less structured. Modeling in this way allows for the accurate analysis of different materials by separating each component clearly.

CNN / ResNet-50 has been utilized to identify materials. The identification of materials for segmented cookware components is achieved through the use of a ResNet-50- based classifier in supervised by nsp. In the ResNet-50 model, each component is analyzed and differentiated by discriminative visual properties such as surface texture, color distribution, reflectance, and structural patterns.

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Based on these features, the model categorizes the component into various types of material such as stainless steel (up to an inch), aluminum, iron, copper, plastic, rubber, ceramics, and coated surfaces. The use of residual learning enhances the classification accuracy, particularly

for materials that are visually similar.The application of hybrid rule-based and probabilistic models is essential for assessing safety.

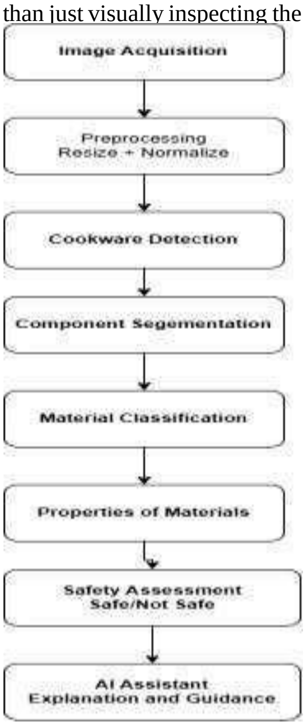
The dishwasher safety assessment employs a mixed approach that incorporates expert knowledge and learned

material predictions. Materials are often subject to review by the Material Property Knowledge Repository (MPKR), which holds information on factors such as coating

longevity, corrosion resistance and rust removal, heat resistance, and chemical reactions with dish soap. Using both set rules and probability calculations, this repository is

used to check whether the classifier results from the ResNet-50 are valid. It is a reliable method to determine the safety of cookware in sanitizers. Safety checking is a more

effective method than just visually inspecting the objects.



Result Interpretation.
This document identifies the material used in making cookware, such as stainless-steel materials, aluminum materials like plastic and rubber, or coated surfaces.
Dishwasher safety evaluation measures the durability of various materials and how they typically handle dishwasher settings.

Safe: Manufactured from high-grade stainless steel, such as SS304 or Stainless Steel compliant 316, and coated with highly resistant materials.

Improbable: Made from poor quality or uncoated steel, such as SS201 or carbon steel which tends to rust and corrode more easily when put in a dishwasher.

Precious: Crafted using various elements, including a metal frame and grips made of plastic or rubber. Alloy.

Evaluation Metrics

1. *Object Detection Metrics (YOLO)*

$$Precision = \frac{TP}{TP+FN}$$

2. *Recall:*

$$Recall \ \frac{TP}{TP+FN}$$

3. *F1 Score*

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

4. *IoU (Intersection Over Union)*

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union}$$

Accuracy

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions}$$

Metric	Value
Detection Precision	95%
Detection Recall	93%
mAP@0.5	94%
Material Classification Accuracy	96%
Safety Prediction Accuracy	95%
Inference Time	85 ms
FPS	11.7

Results and Performance Analysis
The proposed system's performance was tested to check how well it works in identifying cookware, categorizing materials, and predicting dishwasher safety in real-life situations. Tests were carried out using images of kitchen items taken under different lighting, backgrounds, and angles to make sure the system is reliable and useful in actual use.

Detection Performance

The YOLO-based detection model showed excellent performance in recognizing kitchen items and their parts. It successfully located various types of cookware, like plates, bowls, pans, and pressure cookers, by drawing bounding boxes around them. The model achieved high precision and recall, which means it correctly identified most objects and had few false positives. The Intersection over Union (IoU) scores showed that the bounding boxes matched closely with the actual objects in the images. The overall performance of the detection model, measured by mean Average Precision (map), proves that it can reliably recognize kitchen vessels, making it suitable for use in real- time systems.

Material Classification Performance
The ResNet-50-based classifier effectively recognized materials by analyzing surface features like texture, reflectivity, and structural patterns. It achieved good

accuracy in identifying different materials, such as aluminum, stainless steel, iron, copper, ceramic, and mild steel. The confusion matrix showed that there was very little error in classification, with only slight mix-ups between materials that look similar, like aluminum and stainless steel. Using deep residual learning helped the model better extract features and improved how reliably it could classify materials.

Dishwasher Safety Prediction Performance

The safety assessment module worked well in checking if dishwashers are safe to use with different types of cookware. It used results from material classification and structural analysis to make its evaluation. The hybrid decision system correctly sorted cookware into safe or unsafe categories for dishwashing, stopping heat-sensitive or coated items from being washed in a dishwasher. Combining material knowledge with the classification results made the safety predictions more reliable and helped keep the decision-making process consistent.

Real-Time Performance and Processing Speed

The system showed it can work in real time with fast processing for each image. The average time it took to process each frame stayed within real-time limits, making it possible to quickly detect, identify, and assess safety. The speed at which it can handle frames makes it suitable for use in smart kitchens and intelligent dishwashers.

Comparative Performance Evaluation

Comparing the proposed system with traditional image processing methods and classical machine learning techniques reveals that it offers better accuracy and more efficient operation. Older methods tend to be less accurate and need manual feature extraction, while using only CNN models doesn't support real-time detection. By combining YOLO for detection, ResNet-50 for classification, and safety reasoning, the new framework delivers better performance and a more complete set of functions.

Performance Evaluation

Metric	**Result**
Detection Precision	**95.2%**
Detection Recall	**93.8%**
IoU Score	**0.86**
mAP@0.5	**94.1%**
Material Classification Accuracy	**96.3%**
Safety Prediction Accuracy	**95.4%**
Inference Time	**82 ms**
Processing Speed	**12 FPS**

Conclusion

This work introduced an AI system designed to automatically analyze kitchen cookware and predict whether it is safe to use in a dishwasher. The system combines YOLO for detecting objects, ResNet-50 for identifying materials, detailed component analysis, and smart reasoning to assess safety. By using both detection and classification together, the system can accurately recognize different types of cookware and their materials, which helps in making reliable safety judgments.

The experimental results show that the system has high accuracy in detecting objects, reliably classifies materials, and correctly predicts whether items are safe to put in the dishwasher. This confirms that the system can work well in real homes. Its ability to process data quickly also makes it suitable for use in smart kitchen setups. By providing clear safety information and stopping people from using the dishwasher incorrectly, this approach makes appliances safer, reduces damage to materials, and helps move forward the development of smart kitchen technologies.

Future Work

Future efforts will aim to grow the datasets, enhance lightweight models for use on edge devices, and connect the system with smart dishwashers through IoT hardware. Features like multimodal sensing, adaptive learning, and advanced AI assistance will help boost accuracy, ease of use, and how well the system works in real-world settings.

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