A Cost-Effective Deep Learning Workflow for High-Throughput Food Formulation

Adar Fridman and **Serafim Bakalis** and **Remko Boom** *Department of Food Science, University of Copenhagen* {adar, remko.boom}@food.ku.dk
Raghavendra Selvan *Department of Computer Science, University of Copenhagen* raghav@di.ku.dk

Abstract

High-throughput methods can accelerate food formulation design, where combining ingredients to achieve desired textures and stability is central, yet accessible tools for screening gelation are scarce. We present a workflow that combines a 96-well plate platform with sphere displacement tracking and a deep learning-based image analysis pipeline to map gelation behavior in parallel. A YOLOv8 model tracked spheres in each well. Gelatin was selected as a model system to validate the approach. Sphere velocity decreased with increasing concentration, capturing immobilization thresholds and systematic hysteresis between cooling and reheating. Validation against oscillatory rheology showed strong agreement with sol–gel boundaries, with only minor deviations due to discrete temperature steps. This demonstrates that deep learning–assisted sphere tracking provides a reliable, low-cost proxy for rheology, offering a practical tool for rapid, automated food formulation screening.

Keywords: Computer vision, deep learning, soft matter, high-throughput, food formulation, rheology

1 Introduction

Gels are widely used in foods, cosmetics, biomedical devices, and coatings. In foods, gelation governs texture, stability, and consumer perception, making it central to product design. Their tunable properties also enable modifying textures, stability, and controlled release [Banerjee and Bhattacharya, 2012, Caló and Khutoryanskiy, 2015]. Growing demands for healthier, more sustainable products are increasing the need for faster formulation cycles, yet conventional workflows remain slow, resource-intensive, and costly [Cao and Mezzenga, 2020].

Gelation is typically measured mechanically by rheology, which provides detailed insights but is inherently low-throughput and requires large sample volumes. High-throughput experimentation (HTE), originally developed in materials and pharmaceutical research, accelerates discovery through miniaturization and parallel testing [Miracle et al., 2021]. However, applying HTE to soft matter is challenging due to the non-Newtonian rheological properties and its evolving microstructure [Deshmukh et al., 2016].

Artificial intelligence (AI) and machine learning (ML) can reveal formulation–property relationships from high-dimensional data [Schmidt et al., 2019], and have already been applied to phase transitions in complex biological systems [Arter et al., 2022, Liu et al., 2021].

Here, we present a scalable workflow that integrates a 96-well plate platform with deep learning-based motion tracking to monitor gelation. Demonstrated on gelatin, the method enables parallel, low-cost measurements under controlled thermal cycling and validates gelation boundaries against rheology.

2 Method Development & Results

Formulation samples spanning the desired concentration range were prepared in a 96-well plate, with a 3 mm stainless steel sphere placed in each well as a mobility probe. The plate was subjected to controlled cooling and heating ramps (60-5 °C, then reheating) under rotational agitation at 300 revolutions per minute (RPM), while videos were recorded with a digital single-lens reflex (DSLR) camera to capture sphere motion across all wells simultaneously.

2.1 Image Alignment & Tracking

You Only Look Once (YOLOv8) object detection model (Ultralytics; [Redmon et al., 2016]) trained on 676 annotated corner markers (169 images $\times$ 4 markers, mean average precision at 50% IoU (mAP50) > 0.99) which were placed on the plate to enable rotation and translation correction. The dataset was compiled from extracted video frames (1920 $\times$ 1080 px) spanning a range of concentrations, temperatures, and lighting conditions to capture variability. Markers were manually annotated with bounding boxes in Roboflow, and the dataset was split into 80% training, 10% validation, and 10% test sets. After alignment, the images were cropped to the plate region for consistent analysis.

Sphere positions were detected with a second YOLOv8 model (mAP50 $=$ 0.97) trained on $>$6,000 annotated examples using the same protocol and split. Centroid coordinates were mapped to the 8 $\times$ 12 grid, and velocities (mm/s) were computed over 25-frame windows. Mean velocity per condition served as the gelation indicator.

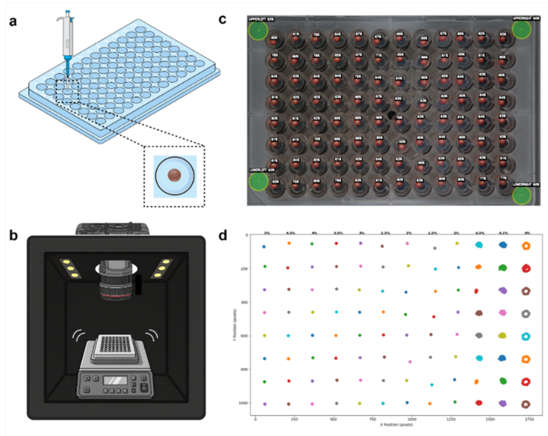

Figure 1: Workflow for gelation screening: (a) concentration gradient in a 96-well plate with spheres, (b) imaging setup, (c) YOLOv8 detections of spheres and markers, (d) trajectories showing mobility at low concentration and immobilization at high concentration.

2.2 Validation on Gelatin

Gelatin, a well-characterized gelling agent in foods, was chosen as a model system to demonstrate the workflow. We hypothesized that sphere displacement would decrease with concentration and temperature, reflecting the known temperature dependence of gelatin gelation. Indeed, sphere velocity decreased with increasing concentration, capturing the progression of the sol-gel transition (Figure 2a). At high temperatures (30-60 °C), the decrease was gradual and viscosity-driven, while at lower temperatures a sharp immobilization threshold emerged. This transition occurred at lower temperatures when lower concentrations were used. This behavior is expected, as gelatin gelation is governed by the helix-coil transition: lowering temperature promotes triple-helix formation and network percolation, leading to a loss of mobility [Bohidar and Jena, 1993]. Complete immobilization corresponded to zero velocity in the dataset, providing a marker of gelation.

Cooling and reheating cycles revealed systematic hysteresis: reheated gels consistently showed reduced mobility compared to freshly gelled ones, while partially melted samples retained residual structure that slowed motion (Figure 2b). This asymmetry highlights the kinetics of network formation and melting and demonstrates that the workflow can resolve not only gelation thresholds but also thermal history effects.

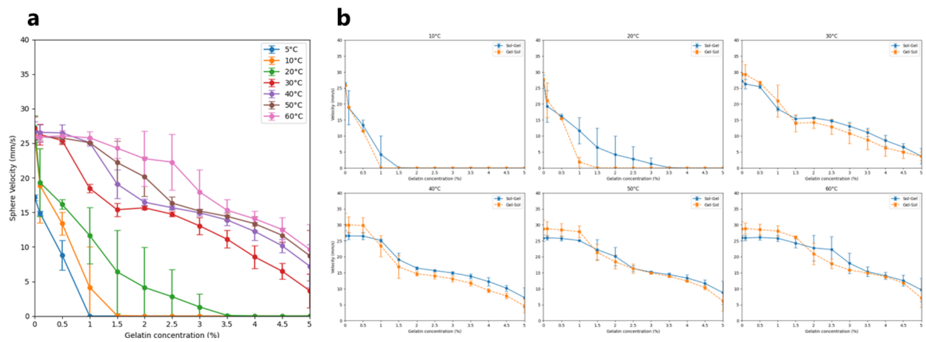

Figure 2: Sphere velocity vs gelatin concentration: (a) mean velocities at six temperatures, (b) cooling (blue) and reheating (orange) cycles."

To benchmark the workflow, oscillatory rheology was performed on identical gelatin samples, defining gelation by the storage (G')–loss (G'') modulus crossover. These values trained a Support Vector Machine (SVM) with a radial basis function (RBF) kernel to generate a phase diagram (Figure 3). Sphere displacement boundaries closely matched rheology, confirming a reliable high-throughput proxy. At low concentrations (1–2.5%), the raw sphere displacement gelation points deviate from rheology because the imaging workflow was performed in 10 °C intervals, limiting sensitivity to transitions occurring between setpoints. This limitation could be addressed with finer temperature ramps for more precise localization.Nevertheless, the fitted boundary captures the overall sol-gel trend and agrees well with rheology, supporting integration into high-throughput pipelines where rheology is a bottleneck.

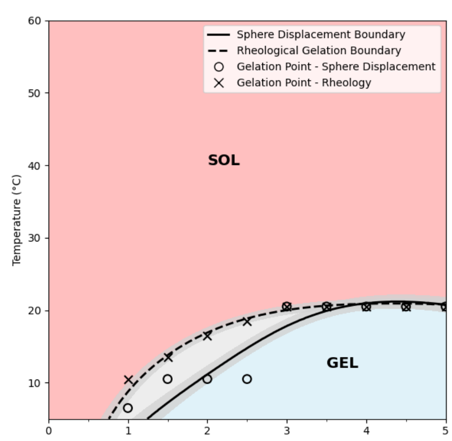

Figure 3: Sol-gel phase diagram of gelatin. Boundaries from sphere tracking (solid) and rheology (dashed) with experimental points and SVM transition zone.

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