AI-Driven Concrete Testing: Designing a Deep Learning Model for Accurate Workability (Slump) Assessment

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Abstract
The concrete slump test is a widely used method for evaluating the workability and consistency of a concrete mix before it is placed on-site. While it ensures that the mix can be effectively compacted, thereby minimizing the risk of voids or structural defects, it can also be labor-intensive. This is especially true on large projects where frequent testing is required. This study proposes a low-waste, image-based alternative using stereo vision and regression modeling to predict slump values. Instead of traditional tools, the method analyzes the spread of concrete discharged through small pipes onto a level surface. Multiple regression analysis reveals that image-derived features—such as spread area ($\beta = 0.0105$, $p < 0.01$), circularity ($\beta = -4.769$, $p = 0.11$), and estimated thickness ($\beta = -2.504$, $p < 0.01$)—can predict slump values with good accuracy. This approach requires only a small concrete sample per test, making it resource-efficient and scalable for frequent automated quality control in the field. These results serve as a proof of concept for future development of deep learning models, paving the way for faster, cost-effective, and environmentally sustainable slump prediction.

Keywords
Stereo vision, Stereo camera, Slump test, Concrete workability, Image classification.

1. Introduction

The concrete slump test is an essential step to evaluate the workability, consistency, and quality of the concrete mixture before it is used on a job site. This property of concrete is generally known to affect the consistency, flowability, pumpability, cohesiveness, and harshness of a concrete mix (Hoang and Pham, 2016). It ensures that the concrete can be easily mixed, placed, and compacted, reducing the risk of voids and structural defects. A correct slump value is critical, as too much water may weaken the concrete, while too little can make it difficult to work with, potentially leading to cracks or poor compaction. The slump test offers immediate feedback on-site, enabling adjustments to the mix if necessary and ensuring compliance with standards, which is vital for the safety, strength, and durability of the final structure. On the other hand, this step is time-consuming and labor-intensive, especially given the rush that occurs when the concrete mix arrives. Moreover, although the slump test itself is inexpensive, the cumulative cost of repeated testing can add up on large projects. Beyond the cost, minimizing concrete use is critical for sustainability, as cement and concrete production generate up to 7 percent of global CO_2 emissions annually (Aprianti et al., 2015). The concrete industry accounts for approximately 50% of global primary energy and natural resources demand (Dixit, 2017), 30% of total waste generation (Pomponi and Moncaster, 2016), 15% of freshwater consumption, and 33% of human-induced greenhouse gas emissions (Rama Jyosyula et al., 2020).

Given these environmental and operational challenges, there is a growing need for innovative and resource-efficient alternatives to the traditional slump test. The increasing emphasis on sustainability and automation in construction workflows highlights the importance of reducing material waste and labor demands (Delmas and Pekovic, 2013). In this context, our research aims to explore the feasibility of using computer vision and image-derived features, such as spread area, shape circularity, and estimated depth, from small-volume concrete samples to estimate workability. This study serves as a proof of concept, demonstrating the potential of these techniques to revolutionize

traditional slump testing. The results of this research will help develop an alternative slump testing method that can be integrated into a computer vision-based app, allowing for quick, accurate testing directly on-site. Ultimately, this solution offers a scalable, field-ready approach that not only improves efficiency but also enhances environmental responsibility in concrete practices.

2. Research Background

Several studies have explored solutions to the limitations of the traditional concrete slump test, which, despite being essential for quality control, can be time-consuming and labor-intensive (Tuan et al., 2021). A modern and increasingly promising alternative involves the use of image recognition and computer vision techniques to estimate workability. For instance, Idrees et al. (2024) utilized image classification models to predict concrete consistency based on visual outputs from the hopper at batching plants, while Ojala and Punkki (2024) analyzed images captured during the mixing process to assess workability characteristics. While these methods offer innovation, their practicality is limited for contractors operating in the field, as they rely on access to concrete production points and high-fidelity imaging setups.

In contrast, this study proposes an image classification framework that predicts slump values at job sites, using depth and color images captured as concrete is released from a small pipe onto a level surface. Unlike earlier efforts, our approach does not require integration at the batching plant or within the truck; instead, it is designed to function as a lightweight and field-deployable diagnostic tool for on-site personnel. This image-based method aims to offer a rapid, low-cost alternative in scenarios where standard slump cones and rods are unavailable, impractical, or unnecessary, such as on small-scale residential or commercial projects. Importantly, the proposed system is not intended to replace the slump test mandated by specifications but to augment current practice by enabling fast consistency checks and minimizing wasted concrete and labor.

To support this framework, we hypothesize that "the spread diameter of concrete discharged from a set height has a strong positive correlation with its slump value." A stiffer mix (lower slump) will spread minimally, whereas a more fluid mix (higher slump) will exhibit a wider spread. The objectives of this study are threefold: (i) to build an image dataset by capturing slump behavior with varying water-cement ratios using an Intel stereovision camera; (ii) to analyze the predictive power of key image-derived features through multiple regression analysis and identify the optimal imaging configuration; and (iii) to lay the foundation for a deep learning-based system that could automate the slump estimation process with minimal material use and setup time. This research contributes a practical and scalable solution toward digitizing a century-old material test, while also advancing theoretical understanding of the visual characteristics of concrete workability.

3. Research Method

This research aims to explore whether image-based features can reliably estimate concrete slump, thereby offering a faster, less wasteful, and potentially automatable alternative to traditional slump testing. To achieve this, we followed the structured workflow illustrated in Figure 1, which includes three major phases: base data collection, masking and feature extraction, and regression modeling.

In the data collection phase, a series of images were captured during controlled concrete discharge experiments using varying pipe and camera heights. This setup was designed to simulate field conditions while generating diverse examples of concrete spread patterns. In the masking and feature extraction phase, we applied manual polygon-based segmentation to isolate the spread region in the RGB images. Corresponding depth values were then extracted from standard binary file format (*.npy*) files generated by the depth camera. From these masked regions, we calculated multiple geometric and volumetric features, such as spread area, perimeter, circularity, and maximum thickness. Finally, in the regression modeling phase, these features were used to predict the real slump values using multiple linear regression. This structured process provided a comprehensive understanding of how visual and spatial patterns

correlate with concrete workability and laid the groundwork for future integration of deep learning methods for real-time classification.

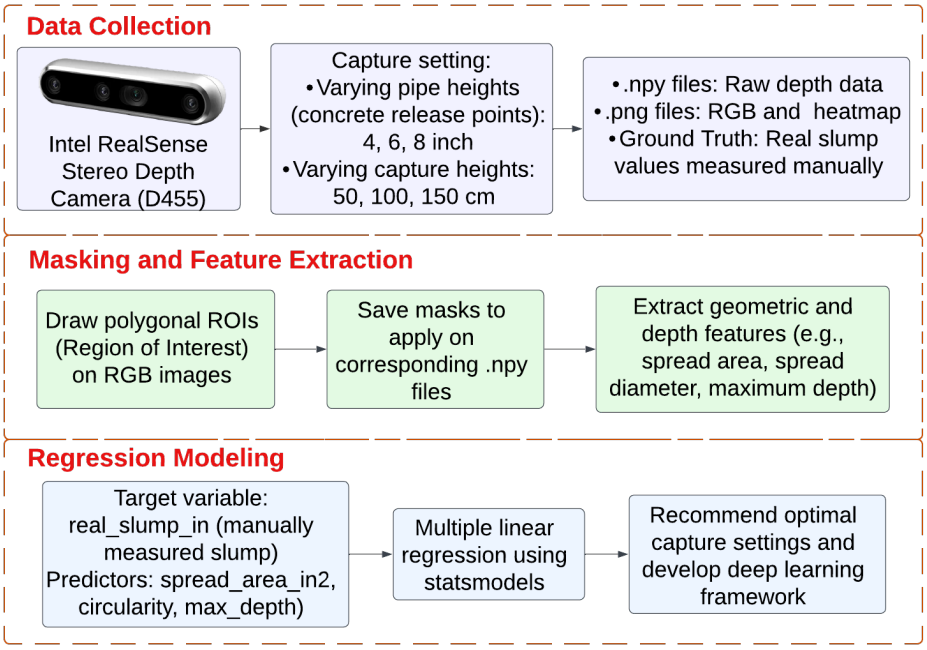

Fig. 1. Research workflow.

3.1 Data Collection Setup

The data collection for this research took place during the Structures-II course in Auburn University's Building Construction undergraduate program. Students in the class prepared a series of concrete mixtures with varying slump values in the field lab as part of an assignment. The mixture information is shown in Table 1.

First, the true slump values for each mixture are recorded using the traditional slump cone method. Then, the concrete sample is released on a level surface (i.e., a wooden board) and concrete spread is measured. To ensure a consistent experiment, we standardized and controlled the amount of concrete by using three different pipe sizes. The pipe sizes are selected as 4x4 inch, 4x6 inch, and 4x8 inch to evaluate the effect of concrete release height. Figure 2 illustrates the dimensions of the pipes used for sampling during data collection.

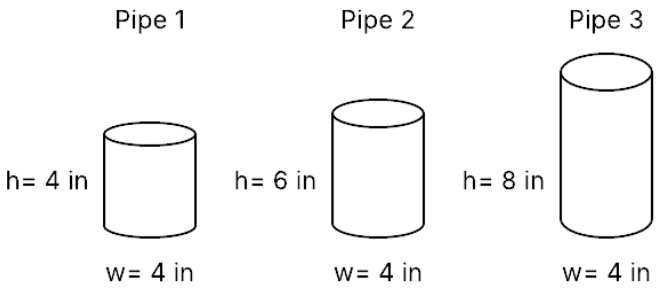

Fig 2. Dimensions of pipes used for sampling.

For each pipe size, the concrete spread is captured with an Intel RealSense Stereo Depth Camera (D455) from three different heights (50, 100, and 150 cm). By doing so, this research aims to suggest the optimum pipe size for the concrete sample and camera height for developing the best-performing prediction model. Figure 3 shows the capture setup and a reference picture for the sample. During the data collection process, multiple images of each concrete slump and its corresponding spread patterns were captured to build a comprehensive image repository for model development.

Table 1. Concrete mixture information and corresponding slump values.

mixture_id	water/cement	true_slump (inch)
mixA	0.60	1.75
mixB	0.70	5.25
mixC	0.80	7.50
mixD	0.90	8.00

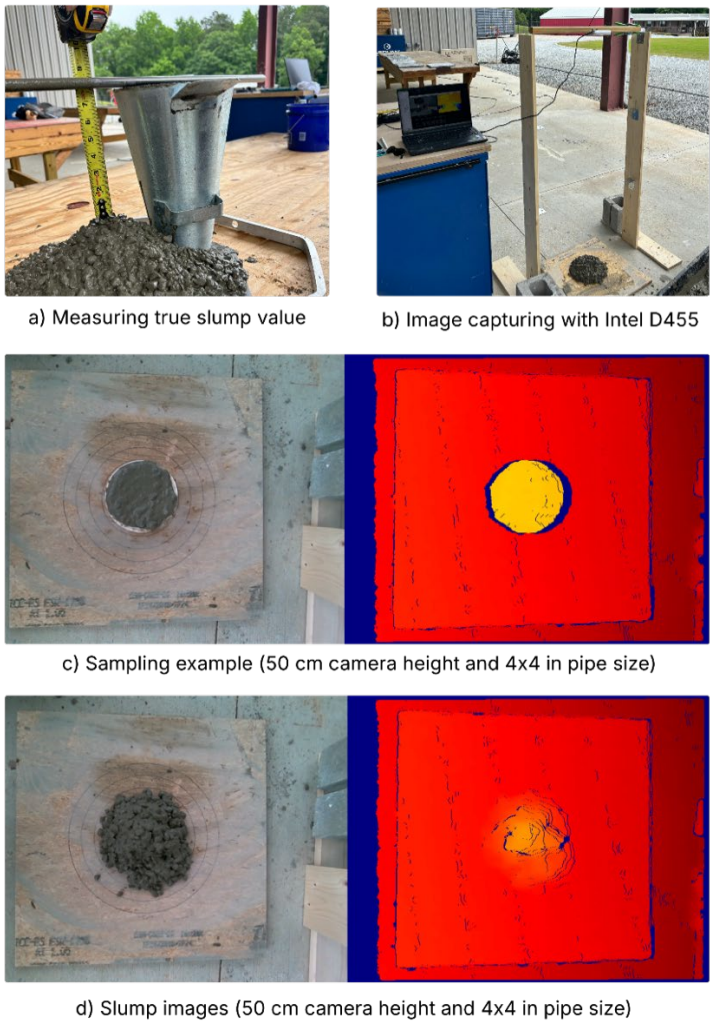

Fig. 3. Data collection process and heatmap examples.

3.2 Data Analysis

To assess the feasibility of using image-based predictions, a multiple linear regression analysis was conducted using manually extracted image features, such as spread area, circularity, and estimated concrete thickness derived from depth data. This preliminary analysis supports the potential of using deep learning techniques, such as convolutional neural networks (CNNs), to automate this prediction task. Deep learning offers advantages over traditional methods by eliminating the need for manual feature engineering and enabling the model to learn complex spatial patterns

directly from raw image data (Li et al., 2019). These capabilities not only improve predictive accuracy but also streamline the analysis of large-scale, high-resolution image datasets.

To accurately extract the depth information, we manually masked the concrete region on the board to avoid background interference. First, the regions of interest (concrete spread) were drawn on RGB images, and saved masks were applied to the corresponding *.npy* files, having depth information. Subsequently, for each masked depth file, we extracted several geometric and depth data, including diameter, mean/min/max depth, and circularity. In total, information from 116 images was extracted.

After the feature extraction, multiple linear regression analysis was performed by using *statsmodels* in the Python environment. For the regression mode, the manually measured slump value was selected as the target variable (y = real_slump_in), and spread area, circularity, and true concrete thickness were used as independent variables (X = spread_area_in2, circularity, true_thickness). Additionally, the results were grouped by pipe height and capture height for evaluating and selecting the best capture settings.

4. Results

Multiple linear regression was performed with 116 observations to predict slump based on spread area, circularity, and true thickness. Table 2 shows the model summary results and indicates the model is statistically significant, $F = 20.37$, $p < .001$, with $R^2 = 0.353$. The significant F-statistics suggest the regression model is significantly better than a model with no predictors (Montgomery et al., 2021). The observed R^2 value of 0.353 suggests that image-derived features explain more than one-third of the variation in slump values, a meaningful result given the complex behavior of concrete and the limited dataset size (Yeh 2007).

The model feature coefficients are listed in Table 3. As their p-value shows, spread_area_in2 ($\beta = 0.0105$, Std error = 0.002, $t = 4.86$, $p < .001$) and true_thickness ($\beta = -2.50$, SE = 0.46, $t = -5.47$, $p < .001$) were significant predictors. These coefficients indicate that for every 1 in² increase in spread area, slump increases by ~0.01 in, and for every inch increase in thickness, slump decreases by ~2.5 in. On the other hand, while circularity was not statistically significant ($\beta = -4.77$, SE = 2.97, $t = -1.60$, $p = .111$) the coefficient indicates that as circularity increases, the slump decreases even though circularity alone may not contribute meaningfully.

Table 2. Model summary.

R^2	Adjusted R^2	F-statistic	Prob	MAE	RMSE
0.353	0.336	20.37	1.32e-10	1.62	1.97

Table 3. Feature Coefficients.

Feature	Coefficient	Std error	p-Value
constant	10.230	2.530	0.00*
spread_area_in2	0.011	0.002	0.00*
circularity	-4.770	2.973	0.11
true_thickness	-2.503	0.458	0.00*

*Significant at 0.01 level

As this study serves as primary research for developing an autonomous deep learning slump classification model, it also examined the optimal data collection settings, focusing on determining the ideal pipe and camera capture heights to gather more data and improve the accuracy of the prediction model. Figure 4 shows the heatmap of the mean absolute error (MAE) for pipe height for sampling and the camera height that illustrates the best combinations, which have less error in the regression analysis. As it illustrates, the best pipe size is 4 in x 6 in. and the best capture height is 50 cm (19.68 in/1.64 ft).

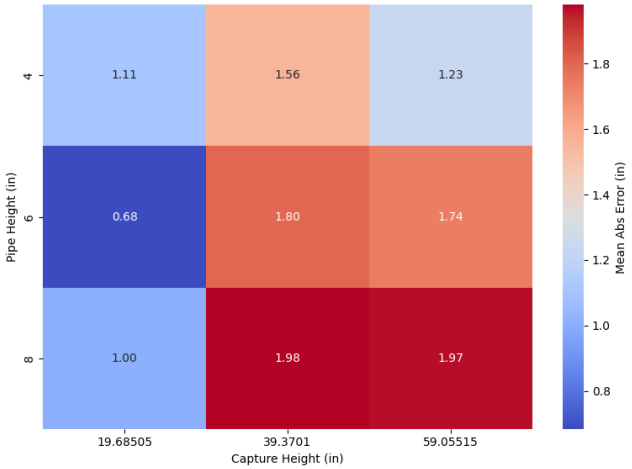

Fig. 4. Mean absolute error by pipe and capture height.

5. Discussion

While construction slump tests are essential, this process consumes time and materials, contributing to resource waste and increasing the carbon footprint of construction activities. This study aims to validate the feasibility of using image-based features, captured from the concrete spread pattern through a small pipe, as inputs for image classification models, such as deep learning. By establishing the predictive potential of these features through regression analysis, we provide an important foundation for future AI-assisted tools that can estimate slump values efficiently and sustainably. For instance, small contractors operating without full testing setups could benefit from this low-cost, portable solution for quick slump estimation, especially in remote or resource-constrained environments.

This study explored the feasibility of predicting concrete slumps using image-derived features extracted from stereo-depth data and RGB overlays. A multiple linear regression model was constructed using three primary predictors: spread area (in²), circularity, and maximum depth (true_thickness_max) of the concrete spread. These features were obtained through manual annotation and calibrated conversion of pixel-based measurements. The model yielded an R^2 value of 0.353, indicating that approximately 35.3% of the variation in actual slump values could be explained by the selected features. While this represents moderate explanatory power, it is consistent with expectations for physical systems characterized by complex, nonlinear interactions and image-based noise (Zheng et al., 2020). The model also achieved a mean absolute error (MAE) of 1.62 inches and root mean square error (RMSE) of 1.98 inches, suggesting reasonable prediction capability, especially given the small sample size and early-stage dataset. The F-statistic (20.37, $p < 0.001$) confirmed that the model significantly outperformed a null model (with no predictors).

The results of the regression analysis indicate that image-derived features such as spread area, circularity, and estimated concrete thickness can be used as features when estimating slump. Accordingly, this research suggests the feasibility of an image-based approach using a much smaller concrete sample compared to the conventional slump test. These findings validate the use of computer vision-based regression for early-stage slump approximation. Importantly, this regression model is not the final predictive system but instead serves as a validation step before implementing deep learning. By identifying which features have significant explanatory power, we gain confidence that visual indicators of spread shape and thickness contain signals relevant to concrete workability.

However, the moderate R^2 value also implies that linear models may not fully capture the complex relationships between physical spread patterns and true slump values. Given the nonlinear nature of concrete behavior and variability in surface textures (Nardelli et al., 2019), more flexible modeling approaches, such as nonlinear regression or deep learning, may offer improved performance. These models can better accommodate feature interactions and subtle variations within images that are difficult to capture through handcrafted variables alone. Thus, while the current regression analysis provides a valuable validation step, future work should explore nonlinear modeling to enhance interpretability and accuracy in slump prediction from spread images.

Moreover, this research identifies an optimal camera height for data collection to support future model development. We observed that a camera height of 0.5 meters yielded the lowest prediction error for estimating true concrete slump. This finding aligns with the work of Tuan et al. (2021), who recommended a working camera height between 1.7 and 1.9 meters when capturing slump behavior using a 30 cm (~12 in) drop height. Our results align with

their findings, as our data were collected from pipes with a 4 inch diameter and height of 4, 6, and 8 inches, indicating that lower release heights may benefit from proportionally lower camera heights to enhance prediction accuracy.

6. Conclusions

This study presents a novel image-based method for estimating concrete workability, specifically slump values, using stereo vision depth data along with manually extracted geometric features. By capturing spread patterns of small-volume concrete discharges through controlled setups, we demonstrate that features such as spread area and estimated thickness significantly correlate with actual slump measurements. The moderate predictive power ($R^2 = 0.35$) validates the use of computer vision for early-stage slump estimation and sets the stage for integrating advanced machine learning models.

Beyond technical contributions, this research introduces a more sustainable and scalable approach to quality control in concrete construction. By minimizing material use and removing the need for full-scale slump cones and rods, this method can streamline on-site testing, reduce environmental impact, and support real-time decision-making. The identification of optimal pipe and camera heights (4x6 inch pipe and 0.5 m camera height) further enhances the repeatability and practicality of this technique.

Future work will involve expanding the dataset, automating the masking and feature extraction process, and deploying convolutional neural networks (CNNs) to improve accuracy. Broader testing across concrete types and environmental conditions will also be necessary to generalize the findings. Ultimately, this work contributes to a future where intelligent, vision-based tools play a central role in construction material testing—supporting efficiency, safety, and sustainability in the built environment.

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