# Real-Time Prediction of Mixing Torque Using Deep Learning

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**Abstract.** Mixing torque reflects the interaction between the mixer and fresh mortar, providing insights into material consistency. Traditionally, obtaining torque measurements requires specialised sensors integrated into mixers, which adds cost and limits their practicality for large-scale or on-site use. To address this, this study proposes a deep learning framework that predicts real-time torque values directly from mixing videos. Instead of relying on specialised sensors or equipment, the model extracts spatial and temporal features from consecutive video frames using a time-series architecture. Specifically, a hybrid ResNet–LSTM model is employed: ResNet encodes spatial features from each individual frame, while the LSTM captures temporal dependencies across sequences of frames. This allows the model to learn how visual changes in the mixing process correlate with the evolving torque. A dataset comprising 21 mortar mixtures with varying compositions was collected, including synchronised video footage and torque measurements recorded throughout the mixing period. Workability, flexural and compressive strength tests were performed after mixing. The model achieved $R^2$ scores of 0.992 (training), 0.989 (validation), and 0.936 (testing), indicating that the model achieved high accuracy with strong generalisation ability across unseen data. The inference time is under 60 ms per 5-frame sequence. The proposed method enables fast, non-contact, and reliable torque estimation, offering a practical solution for intelligent monitoring of mixing processes in real-world settings.

**Keywords:** Mortar workability · Artificial intelligence · Quality control · Data fusion · Real-time monitoring

## 1 Introduction

The flow behaviour of fresh concrete plays a critical role throughout mixing, placement, and consolidation, directly affecting workability, stability, and final performance [1]. Key parameters like yield stress and plastic viscosity influence mixing efficiency, segregation resistance, and material uniformity [2]. Since concrete is the most widely used


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construction material, precise control of its flow behaviour is essential for ensuring structural integrity and long-term durability [3]. Concrete flow behaviour can be measured using laboratory instruments such as rheometers, which provide accurate rheological parameters such as yield stress and plastic viscosity [4]. However, their high cost, complexity, and sensitivity to environmental conditions limit the use of these instruments in field settings.

To address the limitations of conventional flow measurement methods, mixing torque has emerged as a practical and non-invasive indicator for monitoring fresh concrete behaviour in real time. Torque reflects the internal resistance of the material and can be continuously recorded throughout the mixing process [5]. Laboratory studies have shown that optimal workability is usually reached at a distinct turning point on the torque curve that indicates the ideal mixing time [5]. In practice, torque-based monitoring has been adopted in commercial systems like Verifi, which uses onboard torque sensors to estimate slump during transit [6]. The system enables automatic adjustments to admixture dosing in response to real-time consistency changes, reducing the need for manual slump tests and ensuring uniform quality at delivery. Despite its value, mixing torque is rarely used in practice. Accurate measurement requires specialised sensors that are hard to install on existing mixers, especially large or mobile ones. These systems often demand custom setup and calibration, while commercial solutions are costly and not easily adaptable, limiting their use on-site.

To overcome these limitations, this study proposes a video-based deep learning approach for predicting mixing torque. Unlike sensor-dependent systems, this method is non-invasive, cost-effective, and easily deployable without modifying mixing equipment. A CNN-LSTM model captures temporal patterns in video frames, enabling real-time torque estimation without the need for specialised hardware.

## 2 Methodology

### 2.1 Experimental Setup

The mixing torque data was measured using the ToniMIX Visco-Expert mixer, which allows for real-time monitoring of torque throughout the mixing process. To visually capture the mixing behaviour, a GoPro HERO11 camera was employed to record videos at 30 frames per second (fps), with each frame having a resolution of 5312 × 2988 pixels. The camera was strategically positioned adjacent to the bearing of the mixer blade to provide a clear and stable view of the mixing process, as shown in Fig. 1. Due to spatial restrictions in the mixer, the lens placement allowed capturing only part of the area. The mixing continues for 45 min to assess changes in workability over time. To capture the dynamic changes in mixing behaviour while avoiding steady-state periods with minimal torque variation, two video segments were selected for each mortar mixture: 0–15 min and 30–45 min.

The mixing process was conducted in five sequential stages to ensure consistency and reproducibility across all mortar mixtures. In the first stage (0–10 s), water and admixture were added to the binder already present in the mixing bowl. This was followed by premixing of the binder at 62 rpm from 10–40 s to initiate homogenization. Between 40–70 s, sand was gradually introduced while maintaining the same speed. The subsequent

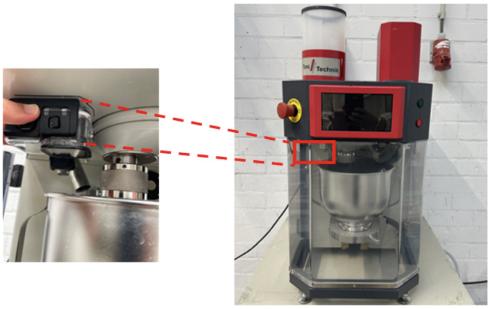


**Fig. 1.** Experimental setup for fixing the camera during mixing video collection.

stage involved mixing at a higher speed of 125 rpm from 70 to 160 s to ensure thorough homogenization of the complete mortar mixture. Finally, from 160 s to 2700 s (45 min), the mixture was mixed at 62 rpm, allowing for continuous monitoring of torque evolution throughout the entire mixing duration.

A total of 21 mortar mixtures (M1–M21) were prepared, all sharing the same mix design. The only varying parameters were the polycarboxylate ether (PCE) chemistry and superplasticizer content. The superplasticiser content ranged from 0 to 0.24% by weight of cement. The corresponding superplasticiser dosages vary from 0 to 1.68 g solid content, with the highest amount used in M2. The water to binder ratio was kept constant at 0.5, with the mixing water being adjusted to account for the water contained in the superplasticiser. The workability of the fresh mortar was evaluated using the slump flow test (NEN-EN 13395–1) without the jolting step of the flow table.[7]. For the hardened state, prismatic specimens were prepared and tested in accordance with NEN-EN 196–1 [8].

### 2.2 Dataset Preparation

Mixing torque data was collected for 20 mortar mixtures (excluding M1). The M1 mixture, which was prepared without a superplasticiser, exhibited a torque curve distinctly different from all the other mixtures. For each mixture, time-series data were analysed to extract total mixing time and corresponding torque values. Meanwhile, mixing videos for each mixture were extracted into frames, and each image was resized to 640 × 320 pixels. It was then converted to a grey scale to further reduce computational cost and improve training efficiency. Since video recording began before torque measurement, frame data were carefully synchronised with torque readings using the recorded mixing start time to ensure accurate alignment.

The input comprises sequential video frames, with a sequence length of 5 frames. The output is the mixing torque recorded within the corresponding second. To improve training quality and remove irrelevant background elements (e.g., reflective mixer parts), a Region of Interest (ROI) was applied to isolate the central mixing zone. The pixel coordinates of ROI are top-left (0, 120), top-right (0, 520), bottom-left (190, 120), bottom-right (190, 520). To cover the full torque range, video frames were extracted from 80–250 s after sand addition for high-torque data, and from 2000–2100 s for low-torque data. A total of 5210 data samples were extracted from the mixing videos, with 80% allocated for training and 20% reserved for validation. The testing dataset (not used in model development) was built from video frames and corresponding torque values collected between 2650 and 2700 s, totalling 455 samples.

### 2.3 Deep Learning Analysis

The proposed model integrates a ResNet-50 backbone with an LSTM network to predict torque values from mixing video sequences. Each frame in the input sequence is first processed by ResNet-50, pretrained on ImageNet, to extract a 512-dimensional feature representation. The resulting sequence of feature vectors is then fed into an LSTM with a hidden size of 128 to capture temporal dependencies. Finally, the hidden state at the last step is passed through a fully connected layer to regress a single torque value. All experiments were conducted on an NVIDIA GeForce RTX 5090 GPU with 24 GB of memory. The training was conducted with a batch size of 8 for 20 epochs. The Adam optimiser was employed with a learning rate of $1 \times 10^{-4}$, and the mean squared error (MSE) loss function was used to optimise the regression objective. The performance metrics were evaluated using MSE, RMSE, and $R^2$ between the predicted and actual values. Figure 2 illustrates the CNN–LSTM network.

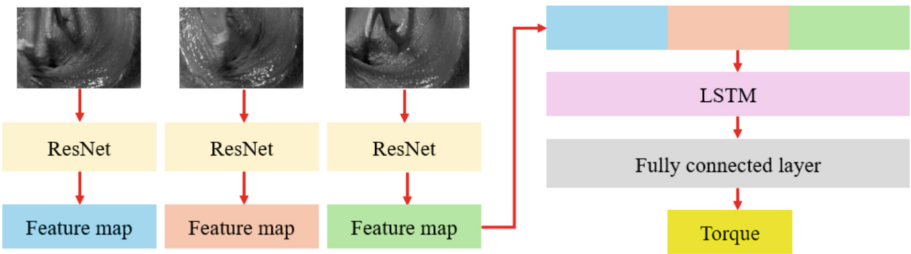



**Fig. 2.** Illustration of CNN-LSTM network for torque prediction.

## 3 Results and Discussions

### 3.1 Experimental Results

Figure 3 illustrates the torque evolution over time for 21 different mortar mixtures (M1–M21) during the mixing process. Each curve represents a specific mixture and shows the torque (in N·m) as a function of time (in seconds). All mixtures exhibit a sharp initial peak, corresponding to the resistance at the start of mixing, followed by a rapid drop and stabilisation. Notably, mixtures such as M1 maintain relatively high torque levels throughout the process, while others, such as M13, stabilise at much lower torque values. This indicates significant variation in the rheological behaviour across different mixtures. The distinct torque profiles reflect differences in mix composition and workability. The data also reveals subtle fluctuations over time, which may correspond to changes in material homogeneity or progress in hydration. All torque curves were recorded during a 2700-s mixing period. The early sharp peak corresponds to the initial resistance after sand introduction. Steady-state torque levels serve as indicators of flow resistance. After 300 s, the mixing torque stabilised, indicating that the mixtures had reached homogeneity.

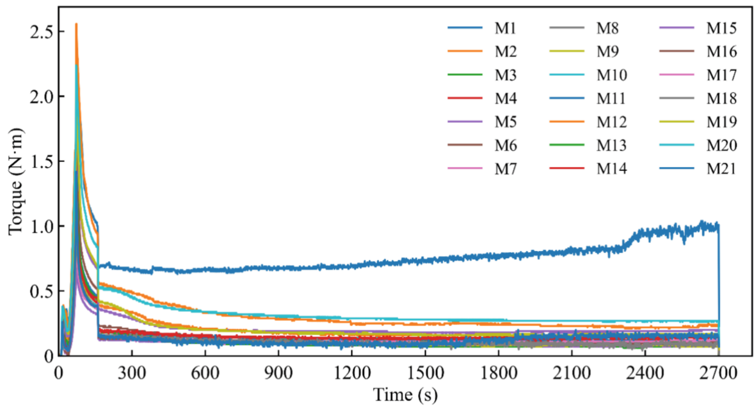



**Fig. 3.** Illustration of mixing torque evolution over time for 21 mortar mixtures.

Figure 4 illustrates the mixing stages and corresponding torque changes before achieving homogeneity. Mixing starts at 10 s, followed by a decrease in torque between 10–33 s as binder particles begin dispersing. At 40 s, sand is added, causing a second increase in torque. Switching to a higher mixing speed triggers a sharp torque rise, peaking at 72 s. As binder particles disperse, the torque gradually decreases until 160 s. At this point, the speed is reduced, resulting in a sudden torque drop, after which the mixture enters a fluid state with stable torque readings.

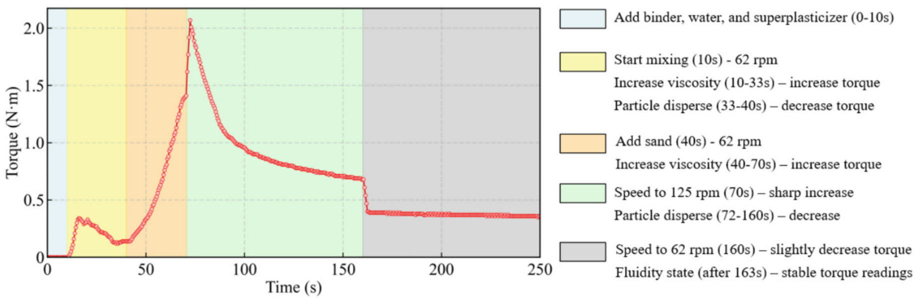



**Fig. 4.** Illustration of mixing conditions at different torques before achieving homogeneity.

The laboratory results included flow diameter at the end of mixing and 28-day flexural and compressive strengths. Slump-flow diameters ranged from 100 to 345 mm, covering a broad spectrum of mortar workability. Since the water/binder ratio was kept constant, the 28-day flexural and compressive results were similar, with an average of 9.62 MPa and 77.2 MPa, respectively, and a standard deviation of 1.56 MPa and 4.2 MPa, respectively.

Figure 5 shows the correlation between final mixing torque readings (45 min) and slump flow diameter, displaying a generally linear trend with an $R^2$ of 0.871, indicating a relatively strong relationship.

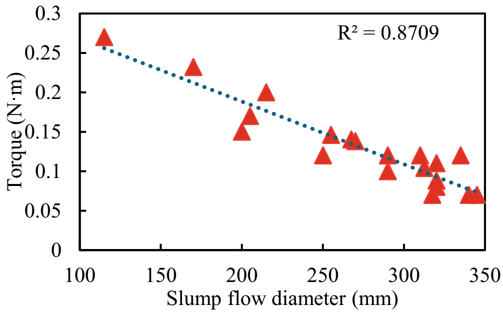



**Fig. 5.** Correlation between final mixing torque and slump flow diameter test results.

## 3.2 Prediction Results

Figure 6 shows the progression of key performance metrics over 20 training epochs for both the training and validation sets, including MSE loss and $R^2$ score. The ResNet-LSTM model exhibited fast and stable convergence during training. Within the first five epochs, the validation $R^2$ increased from 0.9490 to 0.9799; while the MAE and RMSE decreased to 0.0275 MPa and 0.0395 MPa, respectively, indicating that the model effectively learned the underlying data structure early on. The best performance was achieved at epoch 17, with a validation $R^2$ of 0.9886, MAE of 0.0172 MPa, and RMSE of 0.0298 MPa. Throughout the training process, both training and validation losses declined steadily, with no evidence of overfitting, demonstrating the model's strong generalisation ability. The optimal model at epoch 17 was used for testing.

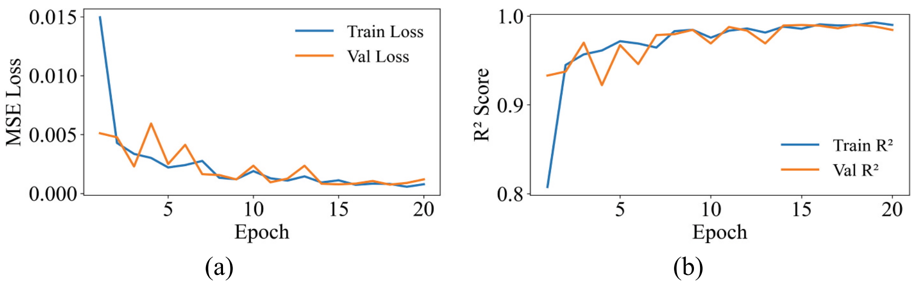



**Fig. 6.** Evolution of performance metrics across 20 epochs: (a) MSE loss and (b) $R^2$ score.

Figure 7 presents the scatter plot comparing predicted torque values with the corresponding ground truth for all test samples. Each point represents a sequence from a specific mixture ID. No significant bias or systematic deviation is observed across the torque range. The testing $R^2$ score of 0.936, MAE of 0.011 MPa, and RMSE of

0.015 MPa further confirm the model's strong predictive capability. Table 1 presents a visualisation of selected predicted results, showing good agreement between the predicted (P) and actual (R) values (unit in N·m). The inference time is under 60 ms per 5-frame sequence.

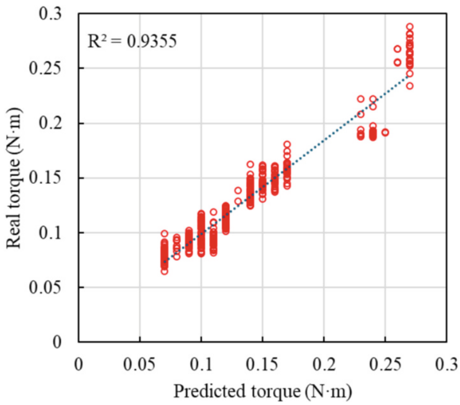
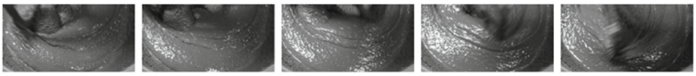
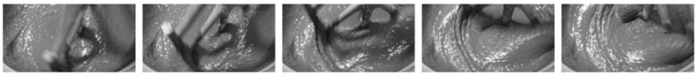
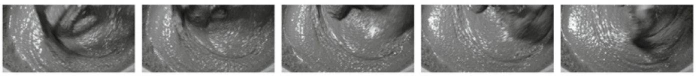
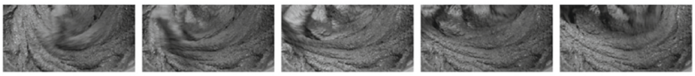
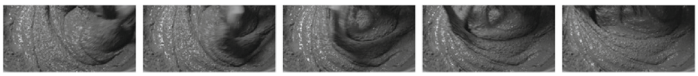



**Fig. 7.** Scatter plot of testing dataset (2650–2700 s interval).

**Table 1.** Visualisation of predicted results.

| ID | Frames 1-5 | R | P |
|---|---|---|---|
| M6 |  | 0.12 | 0.12 |
| M7 |  | 0.11 | 0.09 |
| M11 |  | 0.12 | 0.12 |
| M20 |  | 0.26 | 0.26 |
| M2 |  | 0.16 | 0.15 |

### 3.3 Challenges and Future Research

While the proposed video-based deep learning framework demonstrates strong potential for predicting mixing torque, several challenges remain. Generalizability across different mortar types, mixers, and environmental conditions requires further investigation with more diverse datasets. Second, the adoption of lightweight, real-time models on edge devices will be key to facilitating broader industry adoption. Third, currently the model predicts only torque, while future improvements could involve integrating rheological parameters such as yield stress and plastic viscosity for more comprehensive assessments. These directions will help bridge the gap between laboratory demonstrations and practical on-site applications.

## 4 Conclusions

This study presents a novel, non-invasive approach for real-time monitoring of mortar mixing dynamics by integrating visual data and torque signals through a deep learning framework. A CNN–LSTM architecture extracts spatial and temporal features from video sequences, enabling accurate torque prediction without the need for physical sensors or equipment modifications. Experimental results show that the model achieves high accuracy, with testing $R^2$ reaching 0.936, and inference times under 60 ms per 5-frame sequence, highlighting its potential for real-time deployment. Future research should focus on expanding dataset diversity, improving model generalisation across mixing systems, and integrating predictions of rheological properties such as yield stress and plastic viscosity to further enhance field applications.

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