Automatic Inspection of Green Concrete Quality Using Machine Learning and Cobot

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Abstract—**This paper presents research on development of a novel automatic quality inspection station for concrete products using a cobot equipped with a force sensing finger and embedded machine learning model. After a concrete product is made, it is cured for 28 days to gain full strength. Then, its quality is assessed. However, it is highly desirable to quickly and accurately assess the product quality moments after it comes out of the mold as so called "green", uncured, no-slump concrete to eliminate waste and improve quality. Currently, a human operator inspects the green concrete products by poking and visual inspection as they come out of the molds. This is a highly subjective and often inaccurate approach. Experimental results with the cobot showed 92.3% accuracy in predicting quality of concrete blocks compared to the human accuracy of 50%. The new inspection system can be a viable solution to predict quality of resulting cured concrete blocks from initial tests of green concrete products during production. The system can alert for production problems early on leading to reduced costs and increased product quality when cured.**

Index Terms—**Cobot, concrete, mechatronics, robotics, machine learning, UR10**

I. Introduction

In this research, a novel automatic quality inspection station has been developed for *uncured* concrete products using a UR10 cobot [1] equipped with a force sensing finger and embedded machine learning model.

Concrete products, such as pavers, are made using a machine that can press a concrete mixture into a mold. When the product comes out of the mold, it is uncured. The product is then cured typically for 28 days to reach its full strength. Compression tests are applied to the cured products to assess their quality [2]–[6].

The main challenge is to predict the quality of *cured* concrete blocks using measurements taking from newly made green (*uncured*) no-slump concrete blocks moments after they come out of the machine. There is a significant amount of research in predicting cured concrete quality. Use of non-destructive techniques on uncured no-slump concrete for prediction of cured strength has yet to be investigated. This study proposes a novel approach using a cobot and machine learning model. The new system can rapidly and accurately measure many green concrete products as they come out of the production line. This can increase the quality of the products and alert the facility quickly, if something starts to go wrong in the production before thousands of products are potentially wasted after 28 days of curing. Currently, a human operator stands by the machine to check quality by visually inspecting and poking the green concrete blocks. This approach is highly subjective as the decisions vary due to several factors. Furthermore, he/she cannot measure many blocks as fast as the cobot can. Also, the cobot can evaluate complex geometries of a more intricate product such as the inner walls of a cement block with holes or locking tabs. It can reach into the holes, check vertical side walls or surfaces at any angle. The current research tested flat surfaces for proof of concept.

Several studies have implemented neural network models and Artificial Intelligence (AI) to predict the strength of *cured* concrete. Use of Ultrasonic Pulse Velocity (UPV) combined with Artificial Neural Network (ANN) models showed better accuracy with the ANN models [7]. Rebound hammer and UPV were used in combination for assessing cured concrete quality using ANN [8]–[11]. Ten to fifteen variables were incorporated into an ANN model to predict the compressive strength of self-compacting concrete after curing for 28 days [12]–[14]. Compressive strength of recycled concrete was predicted using ANN model [15], [16]. In another study, researchers were able to decrease the number of variables for the ANN model to six while maintaining good accuracy for predicting green concrete strength [17]. Support Vector Machine (SVM) and ANN models were designed to predict the compressive strength of concrete [18]–[21].

The research involved development of an apparatus for collection of data to train Machine Learning Models (ML). The model has been incorporated into control software so that the cobot can evaluate blocks in real time against the ML model to determine good or bad quality blocks during production. Design of the inspection system along with the experiments conducted with quartz flour and concrete blocks are explained. Results from automatic quality inspection experiments with the cobot are compared to human operator predictions of the same blocks.

II. Measurement System

The measurement system was inspired by nondestructive testing and how the operators check for

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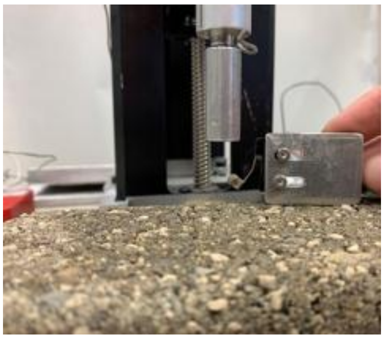
concrete quality. A 0.5 inch diameter aluminum finger was manufactured to replicate an operator's finger touching the concrete surface (Fig. 1a). A FUTEK LCM 100 miniature inline load cell [22] was used as the force sensor as the finger pressed on the surface. The sensor and finger are attached to a ball screw which moved the assembly up/down as a motor rotated the screw. The motor was controlled using a micro step driver and Arduino Uno microcontroller. A template (Fig. 1b) is placed on the block so that force measurements can be taken consistently at three locations (left, middle and right) on each block.

(a) Apparatus with load cell and motor

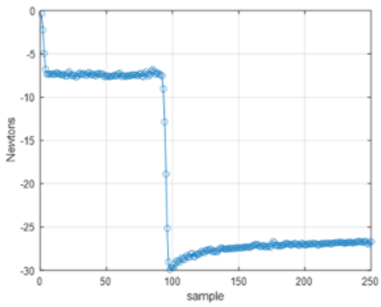
(b) Template to measure forces at three locations

Figure 1. Finger apparatus and template.

The finger apparatus is programmed to first touch the surface of the block then penetrate the concrete 0.5 mm to measure the compressive forces. Each block has a slightly different height. To land the finger on the surface a microswitch was used as shown in Fig. 2a. The switch is held on the surface of the block in the path of the finger. As the finger moves down, it clicks the switch and stops on the surface. The switch is removed by the operator while the finger pauses for two seconds. Finally, it moves 0.5 mm into the concrete for force measurement (Fig. 2b.



(a) Switch is placed on the surface of the block to land the finger on the surface



(b) Compressive force reading before and after the finger is pressed into the block

Figure 2. Finger apparatus details.

III. Automatic Inspection System with Cobot

A. *Inspection of Samples*

Inspection of the concrete samples with the cobot was conducted in a similar fashion as the finger apparatus experiments in Section II. Fig. 3 shows the end-effector of the cobot where a microswitch, load cell and the finger were attached to the cobot wrist with an aluminum bracket.

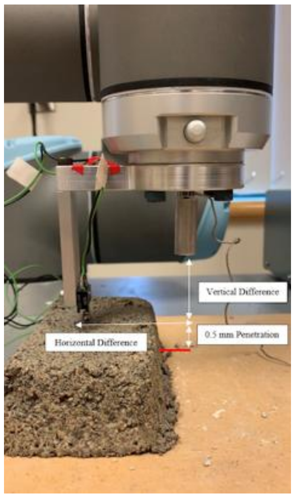


Figure 3. UR10 cobot end-effector with microswitch, load cell and finger.

First, the cobot lowers the switch until it touches the surface of the concrete block. When the switch clicks, the cobot stops and saves the vertical position of the fingertip. Then, the cobot moves the finger over to the position where the microswitch touched the concrete surface. The finger is pressed vertically into the surface 0.5 mm, cobot is paused and sensor readings are recorded. The process is repeated for the left, center, and right force measurements for each block. Finally, the data are sent to the machine learning model to determine the quality of the concrete sample.

B. *Machine Learning for Classification*

This research involves a classification problem where force measurements from concrete blocks are used to determine if a given block is good or bad quality. K-Nearest Neighbor (KNN) algorithm has been used in the cobot experiments. This is a simple machine learning algorithm that is easy to implement and can solve classification problems [23], [24].

The algorithm can determine a discrete output by selecting the nearest points and tallying their outputs. The output with the highest number of occurrences will be assigned to the unknown data point. A common method to determine the nearest neighbors is through Euclidian distance, where the minimal distance between the test and training data is calculated. The "K" value determines how many points are taken into consideration, which is dependent on the sample size and accuracy desired. Fig. 4 displays a data set trained using the KNN model with different "K" values and two outputs. The model is able to create regions that represent how the model would choose the outputs. The output regions of blue and red begin to differ as "K" is changed, which can impact the accuracy of the classification model. Also, the neighboring data points and inputs can be weighted differently. A common weighting method is multiplying the input by the inverse or squared inverse of the distance ($1/d$, $1/d^2$) [25].

First, the cobot lowers the switch until it touches the surface of the concrete block. When the switch clicks, the cobot stops and saves the vertical position of the fingertip. Then, the cobot moves the finger over to the position where the microswitch touched the concrete surface. The finger is pressed vertically into the surface 0.5 mm, cobot is paused and sensor readings are recorded. The process is repeated for the left, center, and right force measurements for each block. Finally, the data are sent to the machine learning model to determine the quality of the concrete sample.

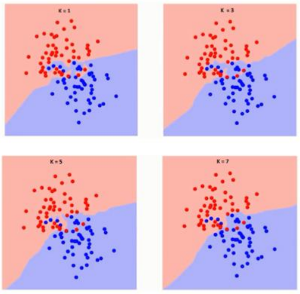


Figure 4. Trained data set for KNN model with different "K" values (K=1, K=3, K=5, K=7) [24].

C. Control Software

The control system consists of two pieces of software: (1) cobot motion program, and (2) program running on PC. The cobot executes motion commands. The program on the PC handles communications with the Data Acquisition Board (DAQ) and the cobot. It also contains the Machine Learning (ML) model to predict the quality of the block when the cobot finishes the force measurements. The user interface shown in Fig. 5 contains two lights. If the ML predicts a good block, the green light turns on. Otherwise, the red light turns on for a bad quality block. The testing area refers to the type of block and actual quality currently being tested. The block quality predicted by the ML model as well as the settings describing the actual block type and quality are recorded to data files.

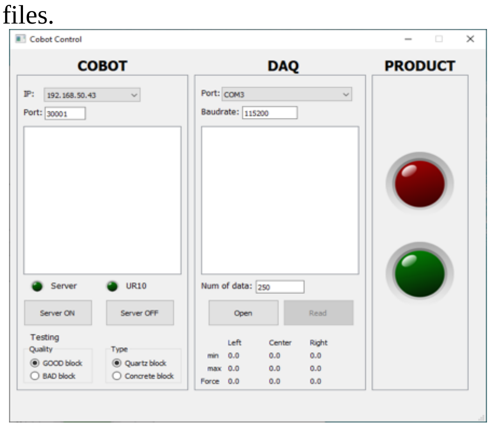


Figure 5. User interface for the control software.

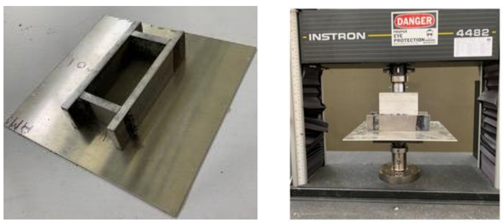
IV. Experiments and Results

Quartz flour has material characteristics similar to cement. However, unlike cement, it does not cure. It is often used as cement substitute in the aggregate mixture during mold design and preliminary testing of concrete products machinery. Since it does not cure, the sample blocks can be broken up and put back into the original mixture for reuse. Consequently, it was decided to use both quartz flour and real cement in the experiments.

A. Preparation of the Blocks

The quartz flour blocks were prepared by hand mixing the appropriate water, aggregates and quartz flour proportions. The recipe is a typical blend used in industry for this type of product. Each ingredient was measured using a scale. A total of 2-3 blocks were made from each mixing to prevent evaporation of water while the samples were waiting to be tested. The mixture was transferred into a 3 x 5 inch tapered nonstick mold with 2 inch depth. Each sample was compacted with a hammer and an aluminum block with similar dimensions as the mold. The resultant compaction level is measured throughout the process on all 4 sides of the block with calipers from the edge of the mold to the surface of the block. Compaction is complete when a certain level is reached, which is dependent on the desired block quality as explained later.

The concrete blocks were prepared similarly to the quartz flour blocks. The main differences were the compaction technique and the mold, as shown in Fig. 6. The concrete blocks were compressed using an Instron tensile tester because it required a much larger force to compact concrete. The tester was first lowered onto the aluminum block surface until it touched the surface. Then, it moved down through the required compaction distance automatically depending on the desired quality of the concrete block. A 2.5 x 5 inch tapered steel mold with 0.5 inch steel plates was built as the mold.



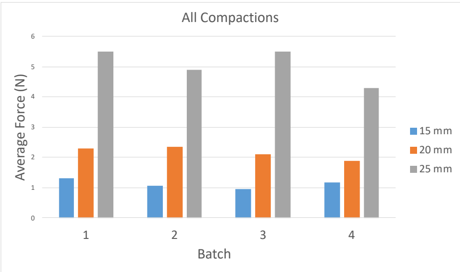
(a) Steel mold to make concrete blocks

(b) Instron machine used in compaction of concrete blocks

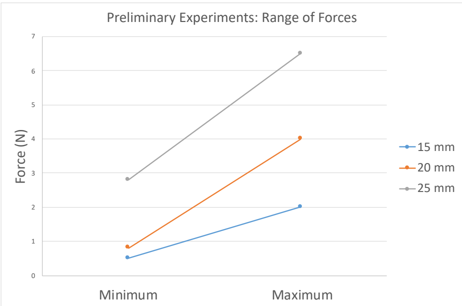
Figure 6. Steel mold and machine used in making concrete blocks.

B. Experiments with the Force Sensing Finger Apparatus

The purpose of these experiments was to determine if there was a relationship between compressive force values and the com- paction level of concrete blocks. A total of 16 blocks were tested with different compaction levels of 15 mm, 20 mm, and 25 mm. The levels refer to the depth at which the sample was compacted when measured from the block's surface to the top edge of the mold. The results in Fig 7a indicate that blocks with greater compaction on average show higher compressive force (4.8N) compared to less compacted blocks (2.1, 1.1N), which is expected. Looking at the range of individual force values in Fig. 7b, there is overlap between 15 mm (0.5N-2N), 20 mm (0.9N-4N), and 25 mm compactions (2.9N-6.5N). For example, a force measurement of 1.1N may come from 15 mm or 20 mm compaction level.



(a) Average force for three levels of compaction



(b) Force ranges for three levels of compaction

Figure 7. Relationship between compaction levels and compressive force measurements.

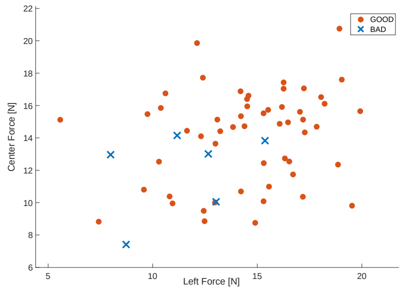
C. Data Collection for Machine Learning Models

These experiments were conducted to collect data so that two machine learning models could be trained for quartz blocks and for the concrete blocks.

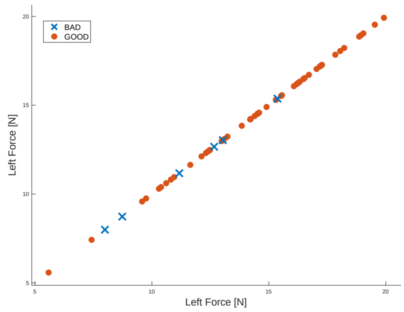
1) Experiments with Quartz Flour Blocks: Sixty quartz flour blocks were made and tested using the finger apparatus in Fig. 1. As the blocks were made, compaction was adjusted so that 90% of the blocks would be good quality. The remaining 10% were made to be bad quality. Twelve random samples (20% of the entire set) were held out of the model and used as testing set to determine the prediction accuracy of the ML model. The remaining 80% of the data were used in training the model.

Fig. 8a shows one view of the collected data where center and left force measurements were plotted for the good (red mark) and bad (blue mark) blocks. It can be seen that there is not a clear separation between the good and bad blocks. Fig. 8b is another view of the same data where left force reading was plotted against the left force reading, which creates a 45 degree line but shows that there is no clear separation. The results verify the importance of implementing a machine learning model and the use of multiple inputs to accurately predict block quality.

2) Experiments with Concrete Blocks: The same procedure and testing parameters were carried out for concrete blocks to collect data for the ML model. The only difference was that the cobot was used to collect the data instead of the finger sensor apparatus. This was necessary due to the need to apply higher forces as concrete blocks were more rigid.



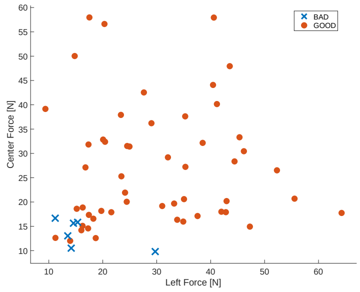
(a) Force data (scatter)



(b) Force data (left-left)

Figure 8. Quartz block force measurements.

The results are displayed in Fig. 9, where the red and blue marks represent good and bad concrete blocks, respectively. The data set had similar overlaps as the quartz flour data set.



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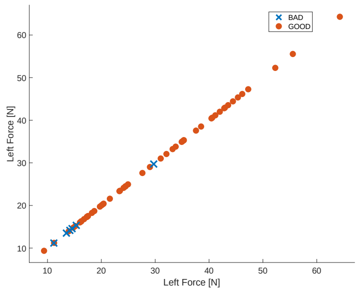

(b) Force data (left-left)

Figure 9. Concrete block force measurements.

D. Experiments with Human Operators

The purpose of the operator experiments was to determine a baseline accuracy of experienced human operators in terms of predicting concrete quality. The results can then be compared to the machine learning model developed to assess the effectiveness of the model.

A total of 60 blocks were tested for both quartz flour and actual concrete blocks. Six operators were asked to predict the quality of 10 blocks at a time. Nine of the blocks were good quality while 1 was bad quality to replicate the yields at typical production facilities. The operators were asked to determine quality based only on poking the blocks. The operators were asked to close their eyes as they conducted the tests to eliminate any visual cues. The blocks were covered until the operators were in place to poke the blocks. Each block was numbered 1-10 and all operators had a different order in which they felt the blocks.

Figure 10. Setup for human operator experiments.

Fig. 10 displays the setup before each operator arrived. The operators were able to poke a good and bad block located at a separate place on the table before the experiments started to recognize the differences in quality and feel. The operators achieved 70% average accuracy on prediction quality (42/60). The accuracy ranged in 50-80% between all operators. Without knowledge of the recipe beforehand or visual cues, it was difficult for them to have high accuracy in predicting the block quality. A production facility would expect higher accuracy to reduce the amount of bad material going to customers or avoid throwing away good quality blocks, especially when facilities produce thousands of blocks daily.

The accuracy of predicting good and bad quality concrete blocks was less than the quartz flour blocks. Only 50% (30/60) of the blocks were identified correctly. The range of accuracy was 20-60%, with only 67% of the bad blocks (4/6) identified correctly. Lower prediction results were mainly due to the higher compaction of the concrete blocks compare to the quartz ones. However, this level of compaction is a better replication of actual compression real concrete undergoes at production facilities. It is clear that relying on a human poke test for quality inspection is not an ideal situation.

E. Experiments with Cobot

In this set of experiments, the cobot system was used to automatically measure forces and predict the quality of the block using the machine learning model built into the control software. The ML models were trained using the experimental data collected earlier as explained in Section IV-C.

1) Automatic Inspection of Quartz Flour Blocks with Cobot: Two experiments were conducted with the cobot to determine the accuracy at which the cobot could predict good and bad quality blocks. The first experiment had 20 blocks with 18 good and 2 bad ones replicating 90% yield similar to typical production facilities. One block at a time was placed on the table. The cobot measured forces at the left, center, and right positions (Fig. 1b). The second experiment involved testing 10 good and 10 bad quality blocks. The goal was to determine the accuracy at which bad blocks could be identified. Previous data sets did not consist of a large amount of bad quality blocks because the experiment aimed to replicate yields at production facilities.

TABLE I. QUALITY INSPECTION RESULTS FOR QUARTZ FLOUR BLOCKS.

	Prediction of Good Blocks		Prediction of Bad Blocks	
	Cobot	Operator	Cobot	Operator
Test 1	16/18 (88.9%)	36/54 (66.7%)	2/2 (100%)	6/6 (100%)
Test 2	9/10 (90%)		8/10 (80%)	
Training Set	10/11 (90.9%)		1/1 (100%)	
Totals	89.7%	66.7%	84.6%	100.0%

2) Automatic Inspection of Concrete Blocks with Cobot: The same experimental approach as in the quartz block case was repeated but using concrete blocks. The results were compared to the operator experiments to determine if the system could improve upon operator predictions (Table II).

TABLE II. QUALITY INSPECTION RESULTS FOR CONCRETE BLOCKS.

	Prediction of Good Blocks		Prediction of Bad Blocks	
	Cobot	Operator	Cobot	Operator
Test 1	18/18 (100%)	26/54 (48.1%)	1/2 (50%)	4/6 (66.7%)
Test 2	10/10 (100%)		8/10 (80%)	
Training Set	10/11 (90.9%)		1/1 (100%)	
Totals	97.4%	48.1%	76.9%	66.7%

In tests 1 and 2, the cobot was given a total of 28 good and 12 bad blocks. Overall prediction accuracy was 95% ((28+9)/(28+12), which is a significant improvement from an operator baseline accuracy of 50% ((26+4)/60). When all test and training sets are combined, the cobot predicted quality of the concrete blocks at an accuracy of 92.3% (48/52), resulting in an increase of 42.3% from operator predictions (50%). Overall, the results are very encouraging. The cobot outperformed operator predictions and showed its reliability and consistency in accurately predicting the block quality.

3) Compressive Strength of Concrete and Comparison to Cobot Predictions: A total of 20 compressive strength tests were conducted on concrete blocks used in the machine learning model. The goal was to determine if the compressive force measurements on green concrete correlated to the compressive strength after curing the same blocks for 28 days.

Each block was numbered. First, all blocks were tested using the cobot and identified as good or bad by the ML model. Then, the blocks were cured for 28 days. Next, they underwent strength testing in accordance with ASTM C140 standards [5]. 18 blocks were good quality while the other two were considered bad quality.

The results of all cured concrete blocks are displayed in Fig. 11. The good and bad blocks are represented by red and blue bars, respectively. The black line indicates the average compressive strength of cured good quality blocks, which was 2,500 psi. This was significantly higher than the average strength of 640 psi for the cured bad blocks. The results show clear separation between good and bad concrete blocks. Block numbers 3 and 4 were determined to be bad after curing and strength testing. These exact blocks were also identified as bad ones by the cobot when they were first made and tested (green, uncured blocks) 28 days ago.

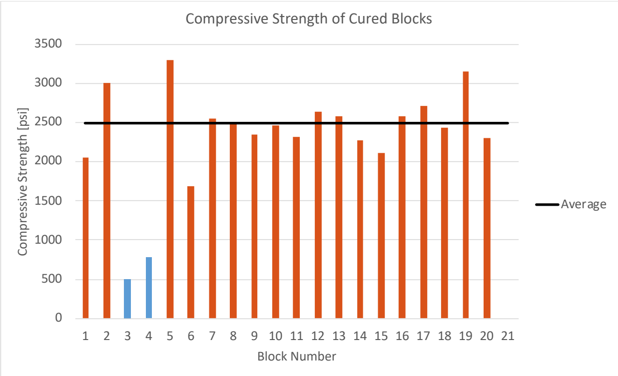

Figure 11. Compressive strength of concrete blocks after curing them for 28 days.

V. Conclusions

In this research, a novel quality inspection system was developed using a cobot with machine learning model. When a concrete product comes out of the mold, it is uncured. The product is then cured typically for 28 days to reach its full strength. The research goal was to predict the quality of *cured* concrete blocks using measurements taking from newly made green (*uncured*) no-slump concrete blocks. There is a significant amount of research in predicting cured concrete quality but use of non-destructive techniques on uncured concrete for prediction of cured strength needs to be investigated. The developed system replicates the poke test by human operators at concrete production facilities as concrete products just come out of the mold. The cobot can inspect many products rapidly and accurately. It can evaluate complex geometries of a more intricate product such as the inner walls of a cement block with holes or locking tabs. Inspection solely by human operators has shown to be an unreliable and inaccurate way to determine concrete quality.

A motorized experimental apparatus with a load cell and finger was developed for testing. Force measurement data were collected from 60 quartz flour and concrete blocks to build a machine learning model (ML) for each type of product. The K-Nearest Neighbor model (KNN) was used to classify the blocks into good or bad quality. In addition, experiments were conducted with human operators predicting the quality of the same blocks using poking tests while keeping their eyes closed.

Experimental results with the cobot showed 88.5% accuracy with quartz flour blocks compared to 70% by human operators. The cobot accuracy was 92.3% compared to the human accuracy of 50% when concrete blocks were tested.

Additionally, twenty blocks were numbered and tested with the cobot when they were newly made. Then, they were cured for 28 days and tested again for compressive strength following ASTM C140 standards. The green blocks that were identified as bad quality by the cobot also tested to be inferior quality bad blocks compared to all other blocks after curing them for 28 days. This correlation and the overall significantly high accuracy predictions of the cobot compared to the human operators are encouraging results. The new inspection system can be a viable solution to predict quality of resulting cured concrete blocks from initial tests of green concrete products during production. The system can alert for production problems early on leading to reduced costs and increased product quality when cured.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

A. Burke designed and built the force measurement apparatus and conducted all experiments. H. Gurocak developed the control software, machine learning model and supervised the research project. Both authors contributed to the manuscript.

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References

[1] Universal Robots. UR10 cobot. [Online]. Available: https://www.universal-robots.com

[2] M. S. Shetty, *Concrete Technology: Theory and Practice*, ND: Chand and Company Limited, 2019.

[3] H. Wong, M. Zobel, N. Buenfeld et al., “Influence of the interfacial transition zone and microcracking on the diffusivity, permeability and sorptivity of cement-based materials after drying,” *Magazine of Concrete Research*, vol. 61, no. 8, pp. 571–589, 2009.

[4] ASTM C39 / C39M-21, “Standard test method for compressive strength of cylindrical concrete specimens,” *ASTM International*, 2021.

[5] ASTM C140 / C140M-20a, “Standard test methods for sampling and testing concrete masonry units and related units,” *ASTM International*, 2021.

[6] ASTM C1716 / C1716M-20, “Standard specification for compression testing machine requirements for concrete masonry units, related units, and prisms,” *ASTM International*, 2020.

[7] M. A. Kewalramani and R. Gupta, “Concrete compressive strength prediction using ultrasonic pulse velocity through artificial neural net- works,” *Automation in Construction*, vol. 15, no. 3, pp. 374–379, 2006.

[8] P. G. Asteris and V. G. Mokos, "Concrete compressive strength using artificial neural networks," *Neural Computing and Applications*, vol. 32, no. 15, pp. 11 807–11 826, 2020.
[9] A. Demir, "Prediction of hybrid fiber-added concrete strength using artificial neural networks," *Computers and Concrete*, vol. 15, no. 4, pp. 503–514, 2015.
[10] R. Madandoust, R. Ghavidel, and N. Nariman-Zadeh, "Evolutionary design of generalized gmdh-type neural network for prediction of concrete compressive strength using UPV," *Computational Materials Science*, vol. 49, no. 3, pp. 556–567, 2010.
[11] M. Shariati, N. H. Ramli-Sulong, M. M. Arabnejad et al., "Assessing the strength of reinforced concrete structures through ultrasonic pulse velocity and Schmidt rebound hammer tests," *Scientific Research and Essays*, vol. 6, no. 1, pp. 213–220, 2011.
[12] M. Nehdi, H. El Chabib, and M. H. El Naggar, "Predicting performance of self-compacting concrete mixtures using artificial neural networks," *Materials Journal*, vol. 98, no. 5, pp. 394–401, 2001.
[13] M. A. Getahun, S. M. Shitote, and Z. C. A. Gariy, "Artificial neural network based modelling approach for strength prediction of concrete incorporating agricultural and construction wastes," *Construction and Building Materials*, vol. 190, pp. 517–525, 2018.
[14] K. O. Akande, T. O. Owolabi, and S. Twahaetal, "Performance comparison of SVM and ANN in predicting compressive strength of concrete," in *Proc. IOSR Journal of Computer Engineering*, vol. 16, no. 5, pp. 88–94, 2014.
[15] B. A. Omran, Q. Chen, and R. Jin, "Prediction of compressive strength of green concrete using artificial neural networks," T. Sulbaran, 2014.
[16] J. Pacheco, J. De Brito, C. Chastre et al., "Experimental investigation on the variability of the main mechanical properties of concrete produced with coarse recycled concrete aggregates," *Construction and Building Materials*, vol. 201, pp. 110–120, 2019.
[17] J. Sobhani, M. Najimi, A. R. Pourkhorshidi et al., "Prediction of the compressive strength of no-slump concrete: A comparative study of regression, neural network and anfis models," *Construction and Building Materials*, vol. 24, no. 5, pp. 709–718, 2010.
[18] J. Sobhani, M. Khanzadi, and A. Movahedian, "Support vector machine for prediction of the compressive strength of no-slump concrete," *Computers and Concrete*, vol. 11, no. 4, pp. 337–350, 2013.
[19] J. Y. Park, Y. G. Yoon, and T. K. Oh, "Prediction of concrete strength with p-, s-, r-wave velocities by support vector machine (SVM) and artificial neural network (ANN)," *Applied Sciences*, vol. 9, no. 19, p. 4053, 2019.
[20] O. Altay, M. Ulas, and K. E. Alyamac, "Prediction of the fresh performance of steel fiber reinforced self-compacting concrete using quadratic SVM and weighted KNN models," *IEEE Access*, vol. 8, pp. 92 647–92 658, 2020.
[21] A. L. Bonifacio, J. C. Mendes, M. C. Farage et al., "Application of support vector machine and finite element method to predict the mechanical properties of concrete," *Latin American Journal of Solids and Structures*, vol. 16, 2019.
[22] FUTEK. LCM100 load cell. [Online]. Available: https://www.futek.com/store/load-cells
[23] Z. Zhang, "Introduction to machine learning: K-nearest neighbors," *Annals of Translational Medicine*, vol. 4, pp. 1–7, 2016.
[24] T. Srivatava. Introduction to K-Nearest Neighbors: A powerful machine learning algorithm (with implementation in Python & R). [Online]. Available: https://www.analyticsvidhya.com/blog/2018/03/introduction-k-neighbors-algorithm-clustering/
[25] O. Harrison. Machine learning basics with the K-Nearest Neighbor algorithm. [Online]. Available: https://towardsdatascience.com/machine-learning-basics-with-the-k-nearest-neighbors-algorithm-6a6e71d01761

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