Design and Evaluation of Virtual Compression Testing Machine Based on Multilayer Perceptron for Vocational-Education Virtual Laboratory

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Abstract **– The weaknesses of Conventional Compression Testing Machines (CCTM) for student practicum are the high costs of procurement, maintenance, electricity, concrete materials, and human/equipment error factors. This research proposed of Virtual Compression Testing Machine (VCTM) based on Multilayer Perceptron that uses 2 hidden layers, 60 neurons with bagging, and other parameters of a Deep Neural Network with RMSE value of 4.738. The application of VCTM has been successfully carried out and there was no significant difference with CCTM. VCTM can be used for various types of concrete with high testing intensity. Lecturers and researchers can use VCTM to conduct research.**

Keywords **– computational education, machine learning, artificial intelligence, virtual laboratory, concrete testing.**

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1. Introduction

Concrete mixtures design practicum in vocational education is carried out conventionally and in a very limited time due to limited testing laboratory facilities. Conventional laboratories are very costly [1] and time-consuming because it requires expensive materials or machinery and is usually taught to small groups [2]. Moreover, high setup and maintenance costs make it difficult to provide laboratory facilities in institutions with limited technical expertise and budgets. This fact is often found in developing countries. For example, in Indonesia, every polytechnic university must serve hundreds of students in one active semester. During the 3 to 4 years study period, each student only experiences one practical opportunity in a practical group consisting of 5 to 6 students. The opportunity to conduct experiments is very low or not sufficient to prepare them before working in the construction industry.

In response, a virtual laboratory (VLab) has been developed to address these challenges [3]. Moreover, Virtual Compression Testing Machine (VCTM) is beneficial in assisting vocational students' learning process, especially during emergencies such as the Covid-19 pandemic. VCTM can be used virtually by the student either individually or in groups, anytime and anywhere.

1.1. VCTM vs. CCTM

To create a virtual laboratorium (VLab), as a virtual learning environment (VLE), a model with high validity is required to ensure that the results are not much different from the conventional laboratory's results.

This can be achieved by creating a VCTM that has the same level of accuracy as the Conventional Compression Testing Machine (CCTM).

VCTM is a very important tool to support concrete compression test practicum without complicated steps, takes less time than CCTM, without maintenance, without destructive testing, and without waste.

In a conventional practicum for one concrete grade, students need to prepare the materials according to concrete mix design which can be obtained from the previous practicum. Those materials are coarse aggregate, fine aggregate, portland cement, water, fly ash, furnace slag, and additives. To make the specimens, students weigh the ingredients accordingly, then mixed and molded mixture is used as a standard mold while keep vibrating it. When the mixture started to harden, the specimen was then removed from the mold and put in a specimen curing tank for several days according to the desired age for testing. Usually, the test is carried out when the concrete is 3, 7, 14, and 28 days old. Specimens that have reached the desired age are removed from the mold and capped on the top and bottom so that the surface is even. Lastly, the specimen is tested for compressive strength of the specimen by feeding it to CCTM until it is destroyed to obtain the concrete compressive strength value. By doing so, the destroyed specimen becomes waste material.

On the other hand, when students use VCTM, concrete compression test practicum can be less complicated and be finished in a short time. Students can predict the strength of concrete quickly and precisely by providing the material composition that fed into the VCTM. The VCTM with its artificial intelligence will perform computations until the specimens' compressive strength value is obtained.

In summary, virtual concrete testing machine research is needed. To our knowledge, there is currently no research on VCTM for concrete testing. Bullard & Stutzman [4] developed Virtual Cement and Concrete Testing Laboratory (VCCTL) with the finite element method. The results showed that not all predictions were following the experiment, especially for the 28-day compressive strength.

This interdisciplinary research is done in two studies based on Computer Application for Building Modeling and Learning Technology. The first study is conducting an experiment to design a computational model of concrete compressive strength which serves as the brain of VCTM. The second study is an evaluation of the VCTM on a limited scale through learning activity to acquire how the system will do and what students' responses are to VCTM.

1.2. Virtual Laboratory for Education (VLE)

The use of computers in VLab has a positive impact in the form of games [5], simulators [6], [7], [8], and virtual machines (VM) [2], [9]. Many researchers suggested that teachers [10] and pre-service teachers [11], [12], [13] design learning by involving VLab for education [14] starting from educational materials, learning activities, and contents to formulate evaluations [12].

One type of VLE is VLab which can facilitate the development of skills of engineering students through simulation and animation before implementation of his/her skills on actual systems [15]. VLab contributes significantly to the current knowledge about the effectiveness of guided inquiry models [16], provides rich learning experiences for students [13], can be used for classroom instruction as well as distance learning, and is a good alternative to expensive equipment [17]. VLab provides adaptive online guidance, allows learners to perform multiple experiments faster, promotes conceptual knowledge, and is cost-effective [18].

From the point of view of the role of computers, there are three categories of virtual laboratories. 1) Virtual reality laboratories that emulate parts or all of the laboratory facilities. These tools can be used alone or in combination with real laboratory sessions. 2) Laboratory that uses part computer simulation and part experimental equipment in a real laboratory environment. 3) Fully software-based virtual laboratories that rely on the whole role of computers, for example, such as playing games. This type of VLab does not simulate the laboratory feeling for the students [2] .

VLab which is included in VLab category 1 is Bristol Chemical Laboratory Sciences [19]. This VLab content is divided into basic and intermediate categories which tend to have interactive diagrams, rather than a photo, depending on the level [20].

Research on VLab category 2 included the hardware-in-loop (HiL) engine test cell simulator and standalone software-based calibration demonstrator. HiL has an embedded system that combines a virtual engine and hardware version such as the Engine Control Unit (ECU) to provide correct and precise machine mapping experience and calibration procedures [21]. Greenlaw et al. [22] used Quality Improvement (QI) simulation for pediatric resident virtual practicum. QI Simulator was feasible and effective, and the QI simulation was well-liked by learners. Hossain et al. [23] deployed The Biology Cloud Lab in an online learning environment by utilizing an online microscope. Students can interact with the microscope via a computer joystick from anywhere.

Researches that are included in category 3 VLab are ViPhyLab applications concerning rotational dynamics materials. Virtual physics laboratory applications could improve students' learning independence and conceptual understanding. Technology-based learning could improve students' conceptual understanding [24]. Mathioudakis [25] created Education on Gas Turbine Principles and Operations. This laboratory is equipped with audio-visual effects so that students can experience actual physical reality. Balamuralithara & Woods [26] developed a VLab as Simulation and Remote Lab. This VLab uses a remote lab server, a set of equipment, and instruments that are used for conducting an experiment. Broisin [27] created the Lab4CE environment, a remote laboratory for computer education, to support the learning of computer science. There are several advantages over real labs, such as flexibility, explanation of a theoretical concept, and repetition.

Most of the practicum in engineering education is carried out by using machines, therefore VLab development requires a VM [2] or a virtual engine [21]. As the number of students increased, Tanyildizi & Orhan [1] created virtual power machines to replace traditional analog voltmeter, ammeter, wattmeter, digital multimeter, and oscilloscope. This VM is ideal for instructional use, and student learning as well as for practical engineering applications.

2. Research Constellation

Computational Engineering Research Constellation is the study of Computational Model of Virtual Machines. To accomplish this, we combine the use of Artificial Intelligence and experimental techniques.

2.1. Computational Model of Virtual Machines

VM development can be done by utilizing statistical models, mathematical models, and soft computing. Moraitis et al. [21] built a HiL engine test cell simulator and standalone software-based calibration demonstrator using mathematical formulas and programming using MATLAB. Tanyildizi & Orhan [1] utilized the mathematical model programmed with Borland C ++ Builder, CGI toolkit, HTML, and ASP programming languages to build an electrical VM. Beghi et al. [6] use mathematical equations before implementing the microcontroller model. Phyton script instructions use to interact directly between the user interface and the pins of the abstract microcontroller model. López & Iglesias [28] built an oscillating water column (OWC) wave energy converter using a soft computing model based on an artificial neural network (ANN).

Burke et al. [2] created a computer-based user interface and linked it to a mathematical model of the engine. The real engine and hardware was replaced with this model issued from research.

Research on the design or development of a virtual concrete testing machine has not been fully explored yet. de Béjar [7] created virtual cement and concrete testing laboratory to estimate both Griffiths' modulus and the cohesive strength of ultra-high-performance concrete with an Extended Finite Element approach. Although this tool can measure the strength of concrete, it is not a concrete compression testing machine.

Computational approaches based on statistical models, mathematical models, and soft computing that have been carried out are still limited to the research for a computational model of concrete compressive strength prediction to find the best model. Thus, this research does not focus only on trying to find the best model but also on designing, and testing algorithms as the brain of VCTM and deploying them into VLab for education.

2.2. Artificial Intelligence Computational Model of VCTM

Research on the computational model of concrete compressive strength has been done many times. The state-of-the-art of computing research is an evolutionary and deep learning model approach due to evolutionary and deep learning models being more advanced to solve the computational problem than other approaches. The evolutionary algorithms that have been implemented are wavelet neural networks (WNN), genetic algorithm (GA), simulated annealing (SA), and fuzzy c-means clustering (FCM) [29]. The deep learning algorithm such as convolution neural network (CNN) was used by Deng et al. [30] and Albawi et al. [31]. Recurrent neural networks (RNNs) was used by Zhou [32], and Multilayer Perceptron (MLP) was used by Ammour et al. [33]. CNN is useful only when the positional and spatial information of a certain feature in the data is important [31]. MLP works better than RNN because RNN is strong only in sequential data [35] and time series data [33], [34]. This research used MLP algorithm. Bagging (bootstrap aggregating) was used together as a hybrid approach to handle noisy data in this study.

For implementing MLP algorithm PyTorch is a publicly available deep learning library [35]. This library was used to implement Deep Neural Networks (DNN). DNN can be constructed by using a perceptron with many hidden layers (HL) with neurons (N) between the input layer and the output layer. On top of that, many regularization methods such as L1 and L2 weight decay and dropout are available to use.

To further improve the accuracy of the model, several advanced methods are also available within this library such as adaptive learning rate and momentum training. Several activation functions, for instance, sigmoid, hyperbolic tangent (TanH), maxout, and rectified linear unit (ReLU) are also available.

To find the optimum weight parameters, AdaDelta optimizer algorithm was used so that the need of choosing learning rate parameters is not needed [36]. In the training process, each computes node trains a copy of the global model parameters on its local data with multi-threading (asynchronously).

3. Research Method

This research method has two stages as shown in Fig. 1. The first stage, is designed VCTM by an experiment with MLP, bagging, activation function, and other DNN parameters to find the best model. Data collection, preprocessing, parameters definition, training, and validating model were completed with PyTorch 1.5.0. The second stage, is the implementation and evaluation of VCTM through concrete compression test practicum for the vocational student.

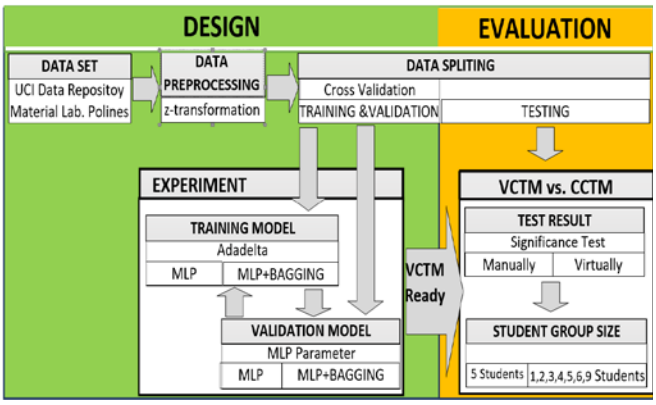

Figure 1. This research method has two stages. The first stage is designed VCTM and the second stage is the implementation and evaluation of VCTM

3.1. Data Collection

Secondary data was collected from the Material Laboratory of Politeknik Negeri Semarang and the UCI Data Repository created by I-Cheng Yeh [37]. The data consisted of 760 concrete mix designs with 6840 components consisting of fine and coarse aggregates, blast furnace slag, fly ash, superplasticizer, cement, water, and varied ages to obtain various specimens.

3.2. Data Pre-processing and Splitting

Because of the variety of measurements that exist in the data, the data will be preprocessed with z-transform.

For each variable, the mean and the standard deviation were first calculated and then all the data input was transformed.

The dataset was shuffled and partitioned into k partitions or k subsets of data. This data then was split into a train set and a validation set by using k-fold cross-validation [38]. One partition is used as the validation set and the rest (k-1) partitions as the training set.

3.3. VCTM Model Design through Computational Experiment

To choose the optimal design parameters this experiment was conducted with two computational phases, model training and model validation. The MLP architecture model was designed by testing the number of hidden layers and the most optimal number of neurons to obtain the lowest error. Several parameters were defined while weights and biases are randomly generated. The parameters were epoch, L1, L2, epsilon, and rho. The model was trained by using the AdaDelta learning algorithm with the training dataset to calculate the prediction. Activation functions ReLU and TanH were used as transfer functions for each layer to avoid vanishing gradients. This prediction was used to calculate the loss by using root-mean-square-error (RMSE). Afterward, the loss was backpropagated to optimize the bias and weight.

To improve the model over noisy data, bagging (bootstrapping) was also used. [39]. Afterward, the result of each model was aggregated with min-pooling based on the error.

After the training process was done, the validation set was used to test the current parameters for overfitting. In this step, the effect of bagging was tested by two models, with and without bagging, by comparing the RMSE.

3.4. Evaluation of the use of VCTM for Concrete Compression Test Practicum

The model with the lowest error rate that had been trained and validated in the previous stage was then programmed into VCTM with a simple display. This smart computing model in the form of VCTM was then applied in the concrete compression test practicum for 30 Polytechnic students who were divided into several groups.

Before the virtual practicum was carried out, students were asked to fill out a pre-test questionnaire to measure their initial perceptions and understanding of the concrete compression test, both conventional and virtual. In the next stage, students listened to the lecturer's explanation of the learning objectives, the concept and process of the concrete compression test both conventionally and virtually, and the evaluation of the concrete compression test practicum. In the next step, students chose the mix design to be tested and entered the mix composition data into VCTM. This concrete mix design data is data from mix designs that have been tested using CCTM.

In the virtual stage practicum, test data were not taken randomly as in the training and validation stage, but rather in a stratified random sampling based on age, material types, material composition, and concrete grade. Another difference is that the test data used by students in the virtual laboratory was taken from data that was not used in the design stage for training and validation of the VCTM computational model. The validation test aims to help the model training process to avoid overfitting while the concrete compression test practicum is a real test to determine the reliability of VCTM.

In this practicum, even though it was in groups of different sizes format, each student was given the freedom to try to do the test independently. Every student was allowed to perform concrete strength tests repeatedly even though the output of the VCTM computation process should always be the same for the same input. The brain implanted in VCTM is based on the same optimal parameters obtained at the design stage. However, in this learning process, students need to be allowed to convince themselves of VCTM performance that they have never encountered before.

Comparing VCTM to CCTM is very important for students to give them a sense of freedom to behave objectively, make assessments, and draw conclusions about the ability of VCTM in learning concrete compression test practicum. They also need to think about future VCTM applications when they work in the construction industry. The output of VCTM was compared with the output of CCTM to determine the error value and various other aspects. At the end of the lesson, students were asked to fill out a post-test questionnaire to measure the knowledge they gained after participating in virtual learning [40] as the first measurement.

4. VCTM Design Result

This study has two results, VCTM Design Results, and VCTM Evaluation Results.

The VCTM design as the first result of this research was obtained through an intelligent computation based on ANN using MLP, bagging, and various DNN parameters.

4.1. MLP Hidden Layers on ReLU and TanH Activation Function

The number of hidden layers and the number of neurons in each hidden layer are the parameters that determine the architecture of the expected model. Based on the preliminary experiment stage, this experiment found the optimal number of hidden layers (HL) between 1HL, 2HL, 4HL, 6HL, 9HL, 12HL, and 15HL, with the activation function of ReLU and TanH, bagging, and the number of 30 neurons in each hidden layer. For other parameters including epoch, L1, L2, epsilon, and rho, the default parameters from the library were used as it is.

For the first experiment, the model was trained without the use of bagging. The result shows that the best number of hidden layers is two layers and the best activation function is TanH with an RMSE of 6.177 while ReLU's lowest error is 6.276. The depth of an ANN does not always guarantee optimum results. In the second experiment, the model was trained with bagging to reduce the effect of noisy data. The best number of hidden layers from the second experiment is two layers, the same as the first experiment. The difference is that the ReLU activation function has better performance than TanH. Bagging and activation function ReLU influence decreasing of RMSE. ReLU RMSE value = 6.036 while TanH = 6.273.

4.2. MLP with Bagging Model

Following the previous results, to obtain the most optimal number of neurons (N), the test tried with 2H10N (2 hidden layers with 10 neurons each), 2H20N, 2H30N, 2H40N, 2H50N, 2H60N, 2H80N, and 2H100N architectures with the ReLU activation function without bagging and maximum epoch 800. The 2HL60N architecture with the number of two hidden layers and 60 neurons has the lowest error with RMSE 4.815.

This experiment was used for determining whether the use of bagging will significantly affect the results. Testing the effect of bagging was carried out through various subsequent experiments with 2H8N, 2H10N, 2H20N, 2H30N, 2H40N, 2H50N, 2H60N, 2H80N, and 2H100N architectures with ReLU activation function. To make the training more efficient, varying maximum epochs were also used. Following MLP architecture without bagging, the optimum epoch value was around 750-800.

Several important results related to the tested model are listed in the following Table 1.

Table 1. RMSE of MLP with bagging and ReLU activation function

	MLP architecture with bagging								
	2HL8N	2HL10N	2HL20N	2HL30N	2HL40N	2HL50N	2HL60N	2HL80N	2HL100N
RMSE	5.200	5.330	5.918	5.477	4.839	5.827	***4.738***	5.740	5.413

Compared with our previous research that has been done, MLP architecture with bagging shows the lowest error value. Table 2 also shows that bagging has the same effect when applied to H2O and MLP, which is to consistently reduce the error value.

Table 2. Effect of bagging when applied to H2O and MLP. MLP with bagging shows the lowest error value than H2O, H2O with bagging, and MLP

Computational Approach	RMSE
H2O	6.674
H2O with bagging	6.385
MLP	4.815
MLP with bagging	***4.738***

The model obtained from this experiment was the final model that has been trained and validated. Experiments on various MLP architectures with bagging obtained the lowest RMSE using 2HL60N architecture with an error value of 4.738. This model error is lower compared to the MLP architecture without bagging with RMSE 4.815. Based on this experiment, it can be determined that the best model is MLP with two hidden layers (2HL) and 60 neurons (60N) with bagging and ReLU activation function. This model can be applied as brain of VCTM to predict concrete compressive strength in a virtual laboratory.

To ensure the first result of this research feasibility, this machine was tested through comparisons against conventional machines and it is used in concrete compression tests practicum on a real scale.

5. VCTM Evaluation Results

The second result of this research was the result of the Learning Evaluation on the implementation of the concrete compression test practicum.

5.1. VCTM is not significantly different from CCTM

As an initial illustration, a conventional concrete compression test practicum is usually carried out in a group of 5 - 6 students using CCTM (see Fig. 2). Conventional practicum is only carried out to test one concrete quality due to limited time and equipment.

Concrete specimens can be 15 cm x15 cm x 15 cm, 20 cm x 20 cm x 20 cm, or a cylinder with a diameter of 15 cm x 30 cm high with a certain age, usually 3, 7, 14, and 28 days. The specimen is placed on the testing machine base and then subjected to constant loading with the addition of the load between 0.2 N/mm2 to 0.4 N/mm2 per second until the specimen is destroyed. The results of the practicum in the form of the maximum compressive strength of the concrete specimen can be seen on the load gauge indicator. The rest of the test results are in the form of specimens that have been destroyed and of course become waste that is difficult to decompose.

Figure 2. CCTM for conventional concrete compression test practicum

The VCTM was then tested by participating students who claimed to have participated in concrete compression test practicum using CCTM. This shows that all students were ready to take part in virtual lab work using VCTM and would have no difficulty responding to evaluation learning activity conducted by VCTM. The use of VCTM in learning is shown by the learning outcomes of the concrete compression test practicum which has succeeded in providing correct understanding for students.

What distinguishes VLab work from conventional practicum was the use of CCTM which was replaced by VCTM. CCTM processes physically while VCTM uses an intelligent computational model to determine the compressive strength of concrete.

In this practicum, each student was given data on 20 concrete mix designs that had been tested using CCTM as listed in Table 3 column "CCTM Test Result - Strength". Each student is given the same data as other students so that they can easily identify if there are differences in results with other students. Students are given the freedom to use and select the data to test the composition of the concrete mix design, but they are expected to carry out the practicum until it is finished according to the learning objectives.

Table 3. CCTM test results vs VCTM test results. RMSE value of VCTM = 5.483

Mix Design Composition									CCTM Test Result	VCTM Test Result	
No	Cement	BF Slag	Fly Ash	Water	SPlastic	Coarse Aggr	Fine Aggr	Age	Strength	Strength	Error
1	310	0	0	192	0	971	850.6	3	9.87	12.95	3.08
2	425	106.3	0	153.5	16.5	852.1	887.1	3	33.4	35.84	2.44
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19	450.1	50	0	200	3	1124.4	613.2	28	39.38	46.91	7.53
20	397	17.2	158	167	20.8	967	633	28	55.65	54.79	-0.86
										RMSE =	5.483

Students then input the composition of the concrete mixed design into the VCTM, run the VCTM, and observe the output. The VCTM used by each student is the same model, so the test results of the VCTM are the same between the students. The hypothesis is that there should be no difference in VCTM versus CCTM results. The test results are written in Table 3 column "VCTM Test Result - Strength".

The results of VCTM tests differ from those of CCTM tests, but it is not significant (Fig. 3). This RMSE value also did not significantly differ from the RMSE value of the validation model of 4.738 (Table 1). There is a difference of 0.745 which is equivalent to the deviation of 0.745 MPa concrete compressive strength.

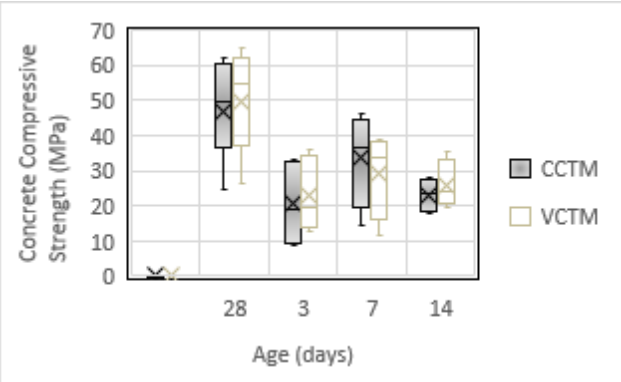

Figure 3. The results of the VCTM test at the age of 28, 3, 7, and 14 days of concrete showed that there was no significant difference in CCTM at the same age

The analysis was conducted to determine the difference and error rate of VCTM relative to CCTM. The results are arranged in order of concrete age of 28, 3, 7, and 14 days according to the concrete strength information which is often used as a reference in the construction industry (Fig. 3). The design of the compressive strength of concrete specimens does not come from the same quality of concrete, so there is no regression analysis based on concrete with the order of ages 3, 7, 14, and 28 days to predict the strength of the remaining concrete.

VCTM also did not differ significantly in changing students' knowledge. It has been tested through pre-test and post-test. The knowledge tested consists of three statements that focus on the VCTM and CCTM function for testing the compressive strength of concrete, not on concrete mix design technology. The test result shown by students who answered correctly to the first statement "The compressive strength of concrete needs to be tested at the age of under 28 days to deal with the possibility of initial loading during the construction process" was 96.7% of students (pre-test) and 96.7% students (post-test). Likewise, the second statement "Before the compression test is carried out, it is necessary to make a specimen with the composition of the concrete mixture according to the required standards and the quality of the mix design" was answered correctly by 93.3% students (pre-test) and 96.7% students (post-test). The third statement "Concrete material and the composition of the mixture affects the resulting compressive strength", was answered correctly by 96.7% of students (pre-test) and 100% of students (post-test). The results show that VCTM is not significantly different from CCTM.

5.2. Impact of VCTM on Practicum Group Size Effectiveness

The behavior of using VCTM is measured based on the facts of student learning and the completeness of student learning outcomes. All students are committed to using VCTM from start to finish and participate in learning evaluations.

The interesting thing discovered in this study is that the ideal number of group members for the VCTM practicum is different from CCTM. This difference can be seen from the success rate of VCTM in maintaining students' knowledge before and after learning activity through pre-test and post-test. If VCTM can provide learning correctly, there should be no difference in students' knowledge when using CCTM compared to VCTM because they all stated that they had participated in CCTM practicum.

However, it is necessary to evaluate beforehand whether the correctness of their understanding when using CCTM is true positive or false positive by conducting a pre-test. The outcome that is undesirable of this practicum is that if VCTM caused students to understand the learning goals incorrectly.

The number of student respondents who took part in this practicum was 30 students. Not all of these students participated in the practicum at the same time but were divided into several groups to obtain the optimal group size. Students were divided into 7 groups with each group consisting of 1, 2, 3, 4, 5, 6, and 9 students. In conventional learning, normally each group consists of 5 students according to the available area around the CCTM. In this virtual practicum, students can use one or more VCTMs with their respective laptops. Each group was given concrete mix design input and concrete compressive strength output with the same learning method.

To the first statement, students in each group answered correctly both in the pre-test and post-test except for students in the group with 1 member. This student answered incorrectly during the pre-test and did not answer or hesitated during the post-test (see Fig. 4).

In the second statement, the group that answered correctly and consistently during the pre-test and post-test was the group with the number of members 1, 2, 4, 5, 6, and 9. In contrast, in the group with 3 students, 2 students answered correctly and 1 student did not answer or hesitated during the pre-test. However, during the post-test, all three answered correctly (see Fig. 5).

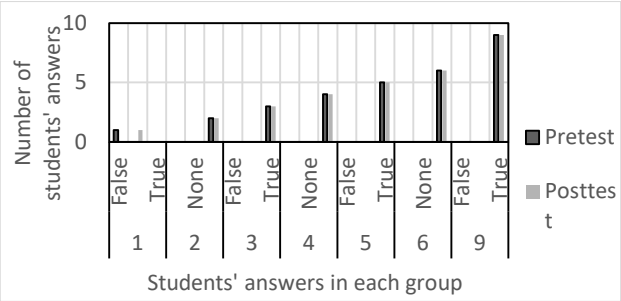

Figure 4. Consistency of pre-test and post-test results for statement 1

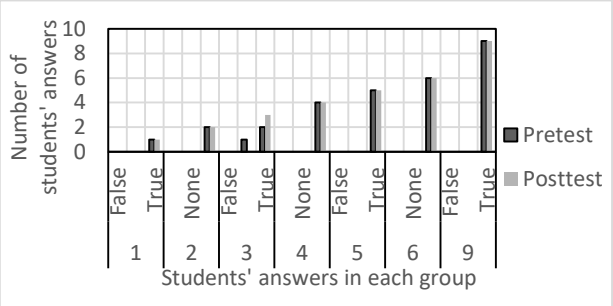

Figure 5. Consistency of pre-test and post-test results for statement 2

In the third statement, groups with 1, 2, 4, 5, and 6 members answered correctly and consistently. In the group consisting of 9 students, as many as 8 students answered correctly and 1 person did not answer during the pre-test, but during the post-test, all of them answered correctly (see Fig. 6).

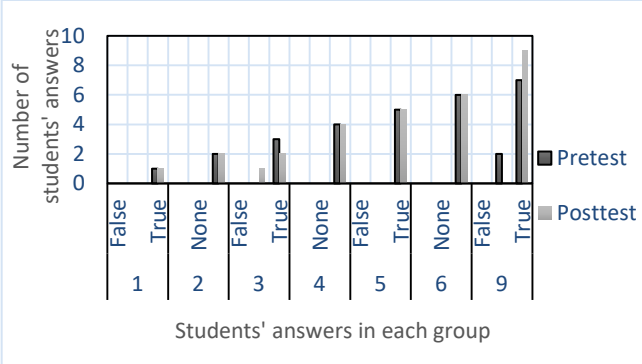

Figure 6. Consistency of pre-test and post-test results for statement 3

In summary, the group whose members consistently answer correctly to all statements is a group consisting of 2, 4, 5, and 6 students (see Fig. 7).

The group with 9 members during the post-test all also answered correctly, although previously during the pre-test there was one member who did not answer or hesitated. The group whose members all answered correctly to all statements is the group with the number of members 2, 4, 5, 6, and 9.

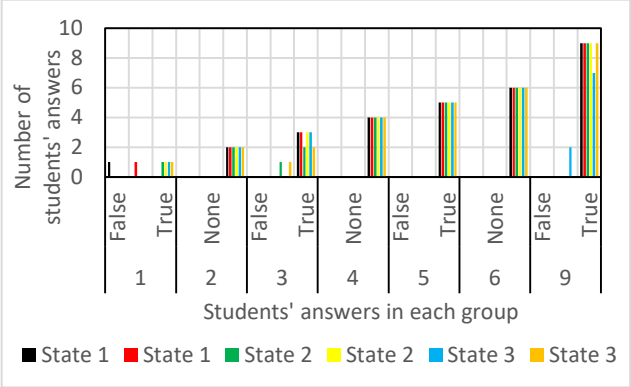

Figure 7. Consistency of pre-test and post-test results for statements 1, 2, 3

6. Discussions

Educational computing research requires two main approaches: computer science and education. The VCTM results of this study use DNN computation based on the MLP algorithm with two hidden layer architecture, each of which has 60 neurons. The depth of a neural network architecture does not always guarantee optimum results, as well as the large number of neurons.

The number of hidden layers and too many neurons can cause the convergence value not to be achieved at optimal global conditions. This can cause the predicted value to be less accurate [41].

The use of the bootstrap bagging function is especially appropriate to reduce the effects of noisy data. This study involved data components of the concrete mix design around 6840 which have a high probability of noise. Regarding the use of the activation function, the ReLU activation function has better results because the output of this function can accommodate the data which has a range from 0 to infinity.

These computational results are important in creating VCTM, which to our knowledge has not been found. There have been many computations for predicting the compressive strength of concrete. The latest development is the research of Wang et al. [30] based on WNN and Deng et al. [31] based on CNN for predicting the concrete compression test. Likewise, de Béjar [7] has built a virtual cement and concrete testing laboratory with the Extended Finite Element modeling approach. However, these studies are not applied in practicum as concrete compression testing machine. From the results of this virtual testing machine VCTM has excellent capabilities to be applied in a virtual concrete compression test practicum.

The application of VCTM as a virtual engine from the concrete compression test practicum has been successfully carried out. The analysis was carried out descriptively to explore and clarify various possible important events that occurred in the study. As stated by Burke et al. [2] virtual engine succeed in transforming learning experience of students by giving them opportunity to put their knowledge into practice. The positive impact of VCTM application can be measured from the fact that conventional laboratories are very costly [1], and time-consuming because expensive materials or machinery are required and are usually taught to small groups [2], [42]. To address this challenge virtual laboratory must be developed [3]. As an answer to these challenges, this study has succeeded in eliminating the drawbacks of conventional practicum by creating VCTM as part of a virtual laboratory. During the Covid-19 pandemic which greatly disrupted the learning process, VCTM became the most appropriate solution to ensure the continuity of concrete compression test learning by individually or in groups.

The number of group members in the concrete mix design practicum which has been limited to only 5 students needs to be reviewed again. The results showed that the number of members of more than 5 students is still effective be applied in one practicum group.

The limitation of group members in conventional practicums is based on the limited area around the CCTM. If there are too many members, there will be group members who do not have the same learning experience as the others.

This is different from practicums that use VCTM which can involve 6-9 students/groups. In this practicum, each student operates their VCTM on their respective laptops. The compressive strength test of the concrete they designed, experiments, observations, analysis, and conclusions can be made based on their wishes. Every student has the same opportunity to do this. The number of practicum group members who use VCTM can be more than CCTM. However, this study limits the number of group members to a maximum of 9 people. This is based on the effectiveness of crowds that can interfere with each other due to activities other than practicum activities.

Another result obtained from this study is that there is no real experience for students in the concrete compressive strength test process. The process consists of the preparation of specimens to the end of the testing process.This process is not the main skill that must be mastered by students in the concrete mix design practicum. The main skill that must be mastered by students is the ability to identify the characteristics of each material and design a mixture composition according to the specified concrete quality and test its strength.

7. Conclusion

During a pandemic such as Covid-19, the virtual laboratory is substantial for educational institutions, especially vocational education that focuses on skills. This study aims to create the VCTM for a concrete virtual laboratory based on artificial intelligence computational models, specifically a DNN using MLP. Experiments to find the best MLP network architecture is done by testing the effect number of hidden layers, the number of neurons, activation functions, and variables associated with DNN parameters. Pre-processing data for MLP network learning was also experimented with in the training and validation by using cross-validation and bagging algorithms. The result shows that the best model is MLP with two hidden layers (2HL) and 60 neurons (60N) with bagging and ReLU activation function, and other parameters described in this study as the brain of VCTM with an RMSE value of 4.738.

The application of VCTM as a virtual engine in the concrete compression test practicum has been successfully carried out. VCTM has an efficient and effective capability to serve groups of 6 - 9 students. All the concrete produced by industry can be utilized at all.

Lecturers and researchers can conduct research on various types of concrete with high testing intensity using VCTM.

The weakness of VCTM is that it does not provide experience in the process of making specimens, treating specimens, and destroying concrete when tested. This experience is needed by students, especially those with student learning styles of physical, active/reflective, visual/verbal, and concrete experience. But this process is not the main skill that must be mastered by students in the concrete mix design practicum. In the future, this research will be continued into a practical learning system based on virtual reality.

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References

[1] Tanyildizi, E., & Orhan, A. (2009). A virtual electric machine laboratory for synchronous machine application. *Computer Applications in Engineering Education, 17*(2), 187–195. Doi: 10.1002/cae.20133

[2] Burke, R. D., De Jonge, N., Avola, C., & Forte, B. (2017). A virtual engine laboratory for teaching powertrain engineering. *Computer Applications in Engineering Education, 25*(6), 948–960. Doi:10.1002/cae.21847

[3] Wolf, T. (2010). Assessing Student Learning in a Virtual Laboratory Environment. *IEEE Transactions on Education*, *53*(2), 216–222.

[4] Bullard, J. W., & Stutzman, P. E. (2006). Analysis of CCRL proficiency cements 151 and 152 using the Virtual Cement and Concrete Testing Laboratory. *Cement and Concrete Research*, *36*(8), 1548–1555. Doi: 10.1016/j.cemconres.2006.05.024

[5] Hsiao, H.-S., Tsai, F.-H., & Hsu, I.-Y. (2020). Development and Evaluation of a Computer Detective Game for Microbial Food Safety Education. *Journal of Educational Computing Research*, *58*(6), 1144–1160. Doi:10.1177/0735633120924924

[6] Beghi, A., Marcuzzi, F., & Rampazzo, M. (2016). A Virtual Laboratory for the Prototyping of Cyber-Physical Systems. *IFAC-PapersOnLine, 49*(6), 63–68. Doi:10.1016/j.ifacol.2016.07.154

[7] de Béjar, L. A. (2019). Virtual estimation of the Griffith's modulus and cohesive strength of ultra-high performance concrete. *Engineering Fracture Mechanics, 216*, 106488. Doi: 10.1016/j.engfracmech.2019.106488

[8] Murphy, M. D. (2016). A modular virtual laboratory for quadrotor control simulation. *IFAC-PapersOnLine, 49*(6), 93–98. Doi: 10.1016/j.ifacol.2016.07.159

[9] Grady, J. L. (2011). The Virtual Clinical Practicum: An Innovative Telehealth Model for Clinical Nursing Education. *Nursing Education Perspectives, 32*(3), 189–194.

[10] Kim, H., & Ke, F. (2016). OpenSim-Supported Virtual Learning Environment: Transformative Content Representation, Facilitation, and Learning Activities. *Journal of Educational Computing Research*, *54*(2), 147–172. Doi: 10.1177/0735633115620197

[11] Canh, L. V. (2014). Great Expectations: The TESOL Practicum as a Professional Learning Experience. *TESOL Journal*, *5*(2), 199–224. Doi: 10.1002/tesj.103

[12] Esteve-Mon, F. M., Cela-Ranilla, J. M., & Gisbert-Cervera, M. (2016). ETeach3D: Designing a 3D Virtual Environment for Evaluating the Digital Competence of Preservice Teachers. *Journal of Educational Computing Research, 54*(6), 816–839. Doi: 10.1177/0735633116637191

[13] Mills, K., Jass Ketelhut, D., & Gong, X. (2019). Change of Teacher Beliefs, But Not Practices, Following Integration of Immersive Virtual Environment in the Classroom. *Journal of Educational Computing Research, 57*(7), 1786–1811. Doi: 10.1177/0735633119854034

[14] Bonadeo, F. S. (2013). Using a virtual classroom in the practicum: Innovations and enhanced practices. *Argentinian Journal of Applied Linguistics-ISSN 2314-3576*, *1*(2), 79-87.

[15] Sotomayor-Moriano, J., Pérez-Zúñiga, G., & Soto, M. (2019). A Virtual Laboratory Environment for Control Design of a Multivariable Process. *IFAC-PapersOnLine, 52*(9), 15–20. Doi: 10.1016/j.ifacol.2019.08.116

[16] Gunawan, G., Harjono, A., Hermansyah, H., & Herayanti, L. (2019). Guided Inquiry Model Through Virtual Laboratory to Enhance Students' Science Process Skills on Heat Concept. *Jurnal Cakrawala Pendidikan*, *38*(2), 259-268.

[17] Gubsky, D. S., Kleschenkov, A. B., & Mamay, I. V. (2019). Virtual laboratory for microwave measurements. *Computer Applications in Engineering Education, 27*(6), 1496–1505. Doi: 10.1002/cae.22164

[18] de Jong, T., Linn, M. C., & Zacharia, Z. C. (2013). Physical and Virtual Laboratories in Science and Engineering Education. *Science, 340*(6130), 305–308. Doi: 10.1126/science.1230579

[19] Bristol, U. of. (n.d.). *Bristol ChemLabS*. University of Bristol. Retrieved from: https://www.bristol.ac.uk/chemistry/courses/dlm/ [accessed: 16 October 2022].

[20] Harrison, T., Slaughter, J., Shallcross, D., & Norman, N. C. (2015). Innovative pedagogies series: A dynamic laboratory manual: Pre-lab online support for practical Chemistry. *Higher Education academy UK Physical Sciences Centre.*

[21] Moraitis, S., Mason, B., Pezouvanis, A., & Ebrahimi, M. (2011). *A Practical, Simulation Based Approach to the Teaching of Engine Mapping and Calibration Fundamentals*. SAE Technical Paper. Doi: 10.4271/2011-01-1109

[22] Greenlaw, C., Jacob, S., & Cheston, C. C. (n.d.). Pediatric Quality Improvement (QI) Virtual Practicum: Adapting a QI Simulator. *MedEdPORTAL*, *16*, 10929. Doi: 10.15766/mep_2374-8265.10929

[23] Hossain, Z., Bumbacher, E., Brauneis, A., Diaz, M., Saltarelli, A., Blikstein, P., & Riedel-Kruse, I. H. (2018). Design Guidelines and Empirical Case Study for Scaling Authentic Inquiry-based Science Learning via Open Online Courses and Interactive Biology Cloud Labs. *International Journal of Artificial Intelligence in Education*, *28*(4), 478–507. Doi: 10.1007/s40593-017-0150-3

[24] Arista, F. S., & Kuswanto, H. (2018). Virtual Physics Laboratory Application Based on the Android Smartphone to Improve Learning Independence and Conceptual Understanding. *International Journal of Instruction*, *11*(1), 1–16. Doi: 10.12973/iji.2018.1111a

[25] Mathioudakis, K., Aretakis, N., Kotsiopoulos, P., & Yfantis, E. A. (2008). A Virtual Laboratory for Education on Gas Turbine Principles and Operation. *Proceedings of the ASME Turbo Expo 2006: Power for Land, Sea, and Air*, 971–979. Doi: 10.1115/GT2006-90357

[26] Balamuralithara, B., & Woods, P. C. (2009). Virtual laboratories in engineering education: The simulation lab and remote lab. *Computer Applications in Engineering Education*, *17*(1), 108–118. Doi:10.1002/cae.20186

[27] Broisin, J., Venant, R., & Vidal, P. (2017). Lab4CE: A Remote Laboratory for Computer Education. *International Journal of Artificial Intelligence in Education*, *27*(1), 154–180. Doi:10.1007/s40593-015-0079-3

[28] López, I., & Iglesias, G. (2014). Efficiency of OWC wave energy converters: A virtual laboratory. *Applied Ocean Research*, *44*, 63–70. Doi:10.1016/j.apor.2013.11.001

[29] Wang, H., Wang, X., Wang, C., & Xu, J. (2019). Concrete Compression Test Data Estimation Based on a Wavelet Neural Network Model. *Mathematical Problems in Engineering*, *2019*, 1–10. Doi:10.1155/2019/4952036

[30] Deng, F., He, Y., Zhou, S., Yu, Y., Cheng, H., & Wu, X. (2018). Compressive strength prediction of recycled concrete based on deep learning. *Construction and Building Materials*, *175*, 562–569. Doi:10.1016/j.conbuildmat.2018.04.169

[31] Albawi, S., Mohammed, T. A., & Al-Zawi, S. (2017). Understanding of a convolutional neural network. *2017 International Conference on Engineering and Technology (ICET)*, 1–6. Doi: 10.1109/ICEngTechnol.2017.8308186

[32] Zhou, D.-X. (2020). Universality of deep convolutional neural networks. *Applied and Computational Harmonic Analysis*, *48*(2), 787–794. Doi: 10.1016/j.acha.2019.06.004

[33] Ammour, N., Alhichri, H., Bazi, Y., Benjdira, B., Alajlan, N., & Zuair, M. (2017). Deep Learning Approach for Car Detection in UAV Imagery. *Remote Sensing*, *9*(4), 312. Doi: 10.3390/rs9040312

[34] Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to Sequence Learning with Neural Networks. *Advances in Neural Information Processing Systems*, *27*.

[35] Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., Desmaison, A., Kopf, A., Yang, E., DeVito, Z., Raison, M., Tejani, A., Chilamkurthy, S., Steiner, B., Fang, L., … Chintala, S. (2019). PyTorch: An Imperative Style, High-Performance Deep Learning Library. *Advances in Neural Information Processing Systems*, *32*.

[36] Kuo, P.H., Lin, S.T., & Hu, J. (2020). DNAE-GAN: Noise-free acoustic signal generator by integrating autoencoder and generative adversarial network. *International Journal of Distributed Sensor Networks*, *16*(5), 1550147720923529. Doi: 10.1177/1550147720923529

[37] Yeh, I.C. (1998). Modeling of strength of high-performance concrete using artificial neural networks. *Cement and Concrete Research*, *28*(12), 1797–1808.

[38] Khaki, S., & Nettleton, D. (2020). *Conformal Prediction Intervals for Neural Networks Using Cross Validation* (arXiv:2006.16941). arXiv. Retrieved from: http://arxiv.org/abs/2006.16941 [accesed: 02 January 2023]

[39] Giessing, A., & Fan, J. (2020). *Bootstrapping ℓ_p-Statistics in High Dimensions* (arXiv:2006.13099). arXiv. Retrieved from: http://arxiv.org/abs/2006.13099 [accessed 01 January 2023]

[40] Granić, A., Nakić, J., & Marangunić, N. (2020). Scenario-based Group Usability Testing as a Mixed Methods Approach to the Evaluation of Three-Dimensional Virtual Learning Environments. *Journal of Educational Computing Research*, *58*(3), 616–639. Doi: 10.1177/0735633119859918

[41] Sheela, K. G., & Deepa, S. N. (2013). Review on Methods to Fix Number of Hidden Neurons in Neural Networks. *Mathematical Problems in Engineering*, *2013*, e425740. Doi: 10.1155/2013/425740

[42] Estriegana, R., Medina-Merodio, J.A., & Barchino, R. (2019). Student acceptance of virtual laboratory and practical work: An extension of the technology acceptance model. *Computers & Education*, *135*, 1–14. Doi: 10.1016/j.compedu.2019.02.010