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Prediction of Compressive Strength of Calcined Clay Based Cement Mortars Using Support Vector Machine and Artificial Neural Network Techniques

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Abstract

Prediction of strength in cement based materials is vital in construction industry as it forms the basis upon which important tasks can be performed such as the time for mortar form removal, project scheduling and quality control among others. The paper reports both experimental and simulated findings on compressive strength of laboratory prepared blended cement mortars. The blended cement was prepared by blending calcined clays with Ordinary Portland Cement (OPC) at replacement levels ranging from 35% to 50% by mass of OPC. In the experimental approach, mortars measuring 160 mm x 40 mm x 40 mm were cast using the blended cement at a water to cement (w/c) ratio of 0.40, 0.50 and 0.60 separately and cured for 2, 7 and 28 days in a laboratory set-up. Compressive strength measurements were taken at each of the curing ages. Part of the experimental data obtained was used to train both Support Vector Machine (SVM) and Artificial Neural Network (ANN) models while the other was used in validation of the models. The trained models were used to predict the 28 day compressive strengths at w/c of 0.35 and 0.65 and also at a cement replacement of greater than 50% and also less than 35 %. The results showed that in training and testing, ANN exhibited stronger potential for predicting compressive strength at w/c of 0.35 and w/c of 0.65 than SVM. In addition, ANN was further found to give more accurate prediction of compressive strength than SVM at all the percentage replacement ranging from 0-60 % with calcined clays. In conclusion, the testing performance of both SVM and ANN was 0.88 and 0.95 respectively.

Keywords: Artificial Neural Network; Blended Calcined Clay; Cement; Compressive Strength; Pozzolana; Support Vector Machine

1. Introduction

The infrastructural development forms a critical component of most national economies globally. The overall performance of cement materials largely depends on the strength development of cement materials. Experimental determination of compressive strength is a time consuming and expensive especially where long curing ages and high pozzolana replacements are involved majorly in blended cements. Therefore, there is need for application of robust techniques that accurately predicts the strength characteristics of different formulations of blended cements where several pozzolana replacements are incorporated.Machine Learning (ML) is a branch of artificial intelligence concerned in development of predictive models without explicitly programming a computer. The predictive model is derived by learning algorithms that search for hidden structure and patterns in the training set data. The inherent patterns in different classes of data aid in developing a mathematical function

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(predictive model) that maps a set of input data to the corresponding target output. ML can be broadly classified into two categories namely supervised and unsupervised learning. In supervised learning, labeled input data and target output is used by a learning algorithm to develop a predictive model while as in unsupervised learning the learning† algorithm figures out the similarities and differences in the presented unlabeled data with an aim of clustering the data based on their structure. Artificial Neural Networks (ANN) and Support Vector Machine (SVM) are two approaches used in supervised machine learning. SVM figures out higher dimensional planes (hyper-planes) that separate different classes of data in a training set. On the other hand, ANN attempts to explore a non-linear mathematical relationship that maps the input data to the corresponding target output. SVM has been outperforming ANN in machine learning tasks until recently when the concept of deep learning was introduced [1]. Deep learning entails using a learning algorithm to implicitly figure out suitable feature vectors to be used in training of the model as well as in prediction using a pre-trained model [2], [3]. ML has been successfully applied in many areas including; computer vision [4], speech recognition[5], natural language processing[6], stock and real estate market forecasting [7]among many other sectors. A limited number of published papers aimed at applying ML in foresting the strength of cement materials at different curing stages have been reported[8]. The performance of cement based materials is largely determined by the compressive strength development of the hydrated cement[9],[10]. Accurate prediction of compressive strength is therefore crucial since it is a key parameter during design and construction[11]–[14]. The present study aimed to investigate the performance of ANN vis a vis SVM in predicting the compressive strength of blended cements containing high content calcined clay as pozzolana and water/cement (w/c) ratio.

2. Materials and Methods

2.1 Materials

OPC (42.5 N/mm^2) was used in the study. Raw clay obtained from Embu County in Kenya was calcined at 800 ^{0}C for four hours in an electrical Muffle furnace. The resultant clay was cooled and finely ground using a laboratory ball mill to achieve 90 µm sizes. Requisite amounts of calcined clay and OPC were mechanically mixed to make the test blended cement at 25, 30, 35, 40, 45 and 50 per cent substitution of OPC. Standard sand was used for mortar preparation. The chemical composition of calcined clay used is shown in Table 2

Table 2: Chemical Composition of Calcined Clay

Oxide	SiO_2	Al_2O_3	Fe_2O_3	CaO	MgO	K_2O	Na_2O	TiO_2	LOI
% Composition	58.4	13.6	10.5	0.4	1.7	2.9	4.1	3.1	3.0

2.2 Methods

2.2.1 Compressive Strength Determination

The mortars were prepared using a laboratory made blended cement that incorporated calcined clay at different substitutions of Ordinary Portland Cement (OPC) in the range of 30-50% by mass of OPC. The mortars were cast at a water to cement (w/c) ratio of 0.40, 0.50 and 0.60 separately and cured for 2, 7 and 28 days in a laboratory set-up. At each of the curing ages, an average of triplicate measurement taken was used as the final Compressive strengths for the mortars.

2.2.2 Machine Learning

The 2, 7 and 28 days laboratory data was processed before it was fitted to the model. This involved selecting the sample size n. In the present study a sample size of 53 was selected. The data was then split into training and testing set based on train test split library available in scikit-learn machine learning library which randomly splits the data using stratification. The split was 80% for the training set and 20% for the testing/validation set. Support Vector Machine (SVM) is a machine learning algorithm focused on modern statistical theory[14], [15]. The implementation was a regression problem and support vector regression was selected. The objective of SVM is

to find a hyperplane in a N-dimensional space (N – number of samples) that distinctly classifies the data points. The implemented SVM had the following parameter values; kernel=linear, regularization parameter = 1, degree of polynomial kernel function = 3.

Artificial Neural Network (ANN) are set of algorithms modelled after the human brain, designed to recognize patterns[16], [17]. It maps inputs to outputs by finding correlations, because it can learn to approximate an unknown function f(x) = y between any input x and output y. In the process of learning, a neural net finds the right f, or the correct manner of transforming x into y.

The implemented ANN was made of 5 layers; one input, one output layer and three hidden layers. It involved passing a rectifier function at each layer; relu (rectified linear unit) was selected for this case. The number of nodes/neurons in the input layer was 128 and for the subsequent hidden layers were 256. The node for the output layer was one since it is a regression problem. Mean absolute error loss and Adam optimizer were used when compiling the model. The summary of the description of ANN Model used is shown in Table 3.

Table 3: Descriptive Summary of ANN Model Used.

| Layer (type)	Output Shape	Param #
Dense_15 (Dense)	(None, 256)	512
Dense_16 (Dense)	(None, 256)	33024
Dense_17 (Dense)	(None, 256)	65792
Dense_18 (Dense)	(None, 256)	65792
Dense_19 (Dense)	(None, 1)	257
Total params: 165,337		
Trainable params: 165,377		
Non-trainable params: 0		

3.Result and Discussion

3.1 Laboratory Results

Table 4 shows the compressive strength results obtained from the laboratory set-up at different replacements of OPC with calcined clays at w/c 0.40, 0.5 and 0.6 separately.

Table 3 (a): Compressive Strength Results from Laboratory set-up Measurements

w/c	Percentage Replacement (%)	Compressive Strength (MPa)		
		2 (Days)	7 (Days)	28 (Days)
	0	24.32	36.09	48.75
	30	18.27	28.68	41.70
0.4	35	16.43	26.41	39.99
	40	14.32	24.32	36.33
	45	12.44	22.36	34.02
	50	10.53	21.07	31.78
	0	20.33	32.1	44.76
	30	14.28	24.69	36.82
0.5	35	12.44	22.42	35.17
	40	10.33	20.33	32.4
	45	8.45	18.37	30.48
	50	6.54	17.08	28.37
	0	17.89	29.66	42.32
	30	11.84	22.25	34.56
0.6	35	10	19.98	33.80
	40	7.89	17.89	29.72
	45	6.01	15.93	27.51
	50	4.1	14.64	25.83

It was observed that addition of calcined clays to OPC resulted to progressive reduction in compressive strength at 28 days. This can be attributed to the reduction in the amount of clinker phases (C_2S and C_3S) that are mainly responsible for strength development in hydrated mortars. Hydration of C_2S and C_3S results in the formation of CSH as shown in Equation (1) and (2) [18].

$$C_3S + H \rightarrow CSH + 2CH \tag{1}$$

$$C_2S + 2H \rightarrow CSH + CH \tag{2}$$
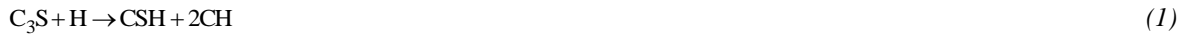
CSH impart strength in cementitious materials. There was an increase in compressive strength with increased curing age. This can be attributed to the continued hydration reaction as indicated by equation (1) and (2) Moreover, in case of the substituted blends at 30-50 % with calcined clays, pozzolan reaction. During the pozzolana reaction, amorphous silica (S) and alumina (A) with CH formed during hydration of C_2S and C_3S to form more CSH as shown by Equation (3) and (4) [19].

$$CH + S + H \rightarrow CSH \tag{3}$$

$$CH + A + H \rightarrow CAH \tag{4}$$

CAH and CSH formed in equation (3) and (4) are also cementious and they impart more strength to the cement mortars albeit at longer curing ages [9].

Increase in the amount of calcined clays form 0-50 % resulted in progressive decrease in strength. This implies that the replacement of OPC with calcined clays results in progressively decrease in the amount of CSH formed hence lowering the strength of the mortars. This shows that in highly substituted blended cements, the added calcined clay was only served as filler material within the hydrated cement matrix rather than acting as a cementitious material. However, shown in table, strength increased with increasing age which indicated the presence of pozzolanic reaction.

At each of the substitution level, compressive strength compressive strength was observed to decrease with increased w/c in the order 0.4>0.5>0.6. This can be attributed to the facts that increase in w/c increases the porosity of the resulting mortars which subsequently lowers their compressive strength.

3.2 Laboratory versus Modelled Compressive Strength Results

The laboratory measurements of strength were taken as the true / accurate compressive strength and used as the reference to evaluate the strength values predicted by SVM and ANN models. The 28 – day laboratory verses modelled compressive strength results are shown in Figure (1-3) at w/c 0.4, 0.5 and 0.6 separately.
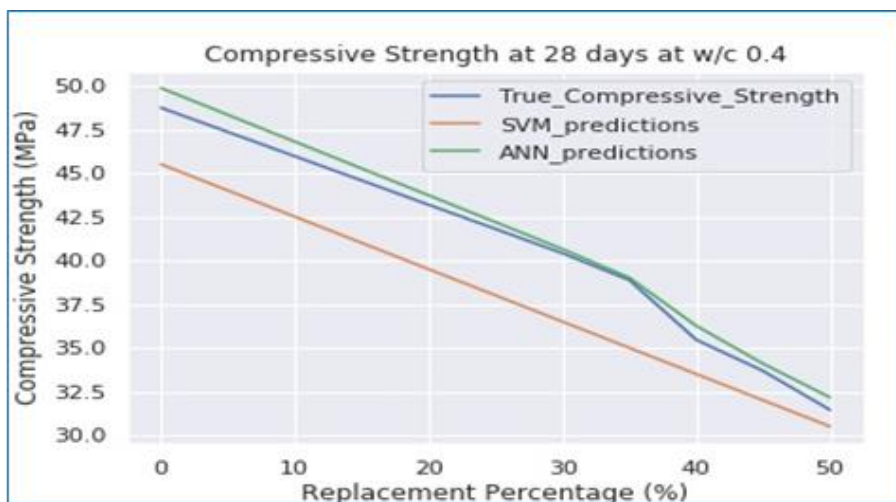

Figure 1: Laboratory verses Modelled Compressive Strength Results (w/c 0.4)
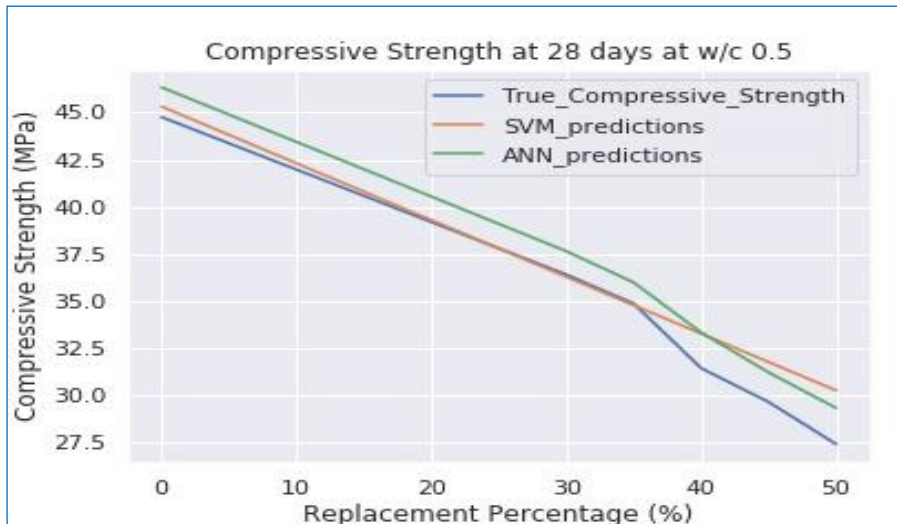
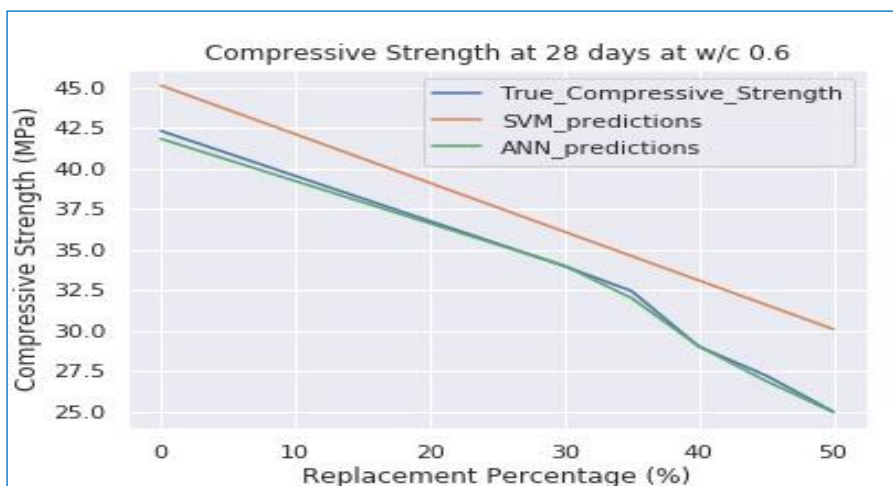Figure 2: Laboratory verses Modelled Compressive Strength Results (w/c 0.5)

Figure 3: Laboratory verses Modelled Compressive Strength Results (w/c 0.6)

Based on Figure 1, at w/c = 0.4, the compressive strength values predicted by the ANN model were closer to the experimental values at all replacement percentages than SVM.

In addition, from Figure 2, at w/c = 0.5, the compressive strength values predicted by the SVM model were closer to the experimental values than ANN at replacement percentages less than 35 %. At replacement level greater than 35 %, the compressive strength values predicted by ANN model were closer to the experimental values than SVM.

Moreover, from Figure 3, at w/c = 0.6, the compressive strength values predicted by the ANN model were closer to the experimental values at all replacement percentages than SVM. In conclusion, it was noted that ANN model was more accurate in prediction of compressive strength for clay based cement where w/c is less than 0.5 or greater than 0.5 (w/c <0.5<w/c) at clay substitution levels considered. The testing performance of both SVM and ANN was 0.88 and 0.95 respectively.

3.3 ANN Model Predicted Compressive Strength (At 28 Day)

The 28- day compressive strength predicted by ANN model at different percentages of replacements with calcined clays is presented in Table 3 (b) in the grey shaded region.

Table 3(b): ANN Model Predicted Compressive Strengths (At 28 Days)

Percentage Replacement (%)	Compressive Strength (MPa)				
	w/c = 0.35	w/c = 0.40	w/c = 0.50	w/c = 0.60	w/c = 0.65
0	52.73	50.94	47.36	44.89	44.13
5	47.71	46.71	42.87	40.94	40.07
10	46.14	44.52	41.63	39.74	38.86
15	44.58	43.89	39.95	38.05	37.15
20	43.3	42.98	38.34	36.42	35.51
25	42.48	41.86	37.90	35.01	34.04
30	42.98	41.70	36.82	34.56	33.69
35	41.95	39.99	35.17	33.80	32.55
40	38.29	36.33	32.4	29.72	28.46
45	35.87	34.02	30.48	27.51	26.47
50	33.67	31.78	28.37	25.83	24.84
55	32.51	30.79	27.78	25.18	24.75
60	32.47	29.85	26.93	24.82	24.4

The ANN model was used to estimate the compressive strength values at 5- 25% replacement of OPC with calcined clays. From the predicted results (in the grey shaded region of table 3(b), it was noted that regardless of the w/c ratio used, the compressive strength decreased with increase in addition of calcined clay added. This observation is consistent with other experimental observations. It is justified because as the replacement percentage is increased, surface area of filler material to be bonded by cement increases thereby reducing strength progressively[20].

The predicted compressive results further show that as w/c increases, compressive strength decreases markedly. This observation is in agreement with the experimental findings. When high w/c is involved, there is a poor packing of cement grains and aggregates which makes the hydrated cement matrix more porous[21]–[23]. Increased porosity of hydrated cement subsequently results in reduced compressive strength of the cement based structure.

4. Conclusion

Based on the study, ANN was found to give more accurate prediction of compressive strength than SVM at all the percentage replacement ranging from 0-60 % with calcined clays. The testing performance of both SVM and ANN was 0.88 and 0.95 respectively.

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