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Estimated of Concrete Compressive Strength by Using Neural Network and Machine Learning

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Abstract: The most fundamental input of the construction sector is concrete, which would be a massively complicated element. Concrete is among the most common structural construction materials due to its strength. Since some manufacturers manufacture out of reach and low quality, there is a growing demand for earthquake-resistant design in the fully prepared concrete industry. Concrete's strength-gaining properties are influenced by a variety of factors. This research aims to use the results of early compressive strength tests to predict strength properties at various ages. The ability to estimate the determination and strength of normal concrete using the early day strength properties result has been examined. Including both concrete and regional concrete mixes, a basic numerical equation forecast the concrete strength at any age is proposed. The goal of this article is to show how artificial neural networks (ANN) and machine learning can be used to forecast the compressive strength of high-performance concrete. On the other side, we'll evaluate the errors of all of the techniques we're using. The dataset used was obtained from the UCI Machine Learning repository. As a result of the research, it was discovered that the Random Forest Algorithm and Artificial Intelligent gives the best performance when all input parameters were used, including cement, slag, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, and age.

Keywords **- Concrete, Strength, Artificial Intelligent, Machine Learning, Performance, Features.**

1. INTRODUCTION

Compressive concrete strength has long been regarded as a quality management index. Concrete quality is usually measured by the concrete cylinder's compressive strength measure. In designing a concrete building, the engineers depend essentially on the signature strength of the concrete. The concrete's characteristic strength is generally referred to for 28 days as the strength of the concrete sample cured. The basic cylinder concentration analyses of concrete usually establish this. Much of the concrete building code also suggests 28 days of design strength.

28 days of building time is an important amount of time to wait, and is important and cannot be ignored to ensure the consistency of concrete. It is also necessary to wait at least 28 days to validate the consistency and strength required. A very simple and accurate method to estimate the end strength of the concrete at an early age (as soon as possible) can help you to understand the consistency and probable weakness of the concrete. It will help you decide whether you want to proceed or control the destruction The following are the author's notebooks: Dr. Ahsanul Kabir, BUET, Bangladesh, Department of Civil Engineering. In this respect, an early decision is a long-standing issue [1].

Since concrete is widely used in construction, its strength must be established. The precise calculation of the strength value was still a crucial problem as concrete consists of an aggregation, mortar, water, and additives. Since concrete can easily be compressed, shipped, mounted, compacted, and lightened, as a structural building material in various colors, surfaces and forms. Until the concrete strength test is modified, it tests the coherence and operability of fresh concrete. Until the concrete strength test is modified, it tests the coherence and operability of fresh concrete. Consistency means that the concrete can be blended, put, compressed, and completed, which is easy and homogenous. The high strength of the concrete is essentially the most critical aspect. At the same time, concrete is supposed to feature such features as economic, chemical degradation resistance, and fire resistance.

In theory, the explicit mathematical input and output relationship has to be well understood to model a structure. Such explicit mathematical simulation in a poorly known method is complex and unclear. The association between the specific force and its constituent characteristics is the basis of the majority of the prediction model proposed [2]. A variety of studies attempted to choose various factors, considering various characteristics and the proportioning of concrete ingredients influencing concrete behavior.

This article tries only to use the results from the early strength test to estimate concrete strength at various ages instead of including other considerations. Concrete intensity is explored about the concrete era and ultimately represented by a basic mathematical model. The model is developed by analyzing the effects of crushing strength tests in standard weight concrete cylinders [3] and then validated by test results in several countries [4,5]. Both of the forecast predictions are good for the real outcome.

2. Related work

The method of concrete gaining strength is a dynamic multi-factor process. In this respect, there are several reports. The researchers have displayed a high level of curiosity in it even today. Knowledge of the concrete strength benefit trend allows the early prediction of concrete characteristic strength and provides an insight into the consistency of concrete conformity to the criteria for construction.

Many enhanced methods have been implemented to resolve the issue of power estimation at various ages, including empirical/computational modeling using the Artificial neural network, genetic algorithm, fuzzy logic, etc., and mathematical techniques. Any research has focused on the use of linear regression to increase prediction accuracy. Linear regression equation (Eq. 1), also used in force projection, is the most often used for water-cement (w/c) about concrete weight.

$$f = b_0 + b_1.w/c \qquad (1)$$

Where f is concrete compressive power, coefficients are b_0, b_1. The source of this equation is the Law of Abram[9] which inspired the development of the following multivariate equation of linear regression.

$$f = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + ... + b_nx_n \qquad (2)$$

Where $x_1, x_2, x_3, ... x_n$ are variable, the variables influencing concrete behavior, such as water-cement ratio, amount of cement (C), amount of rough aggregate (CA) quantity of fine aggregate (FA), etc., in the concrete mix, may be substituted.

The multivariate power equation has been selected in a recent studied [6] as an important model for the prediction of the intensity of various concrete ages. Below is the general format of the equation (Eq.3):

$$Y = a_0 x_1^{a_1} x_2^{a_2} x_3^{a_3} .... x_m^{a_n} \qquad (3)$$

The above-mentioned equation considers that the compressive force for a specific day is a dependent variable on variables that have a major relationship with the intensity of the variable including (w/c), cement (C), water (W), sand (FA), aggregate (CA). It becomes an equation:

$$f_{age=} a_0 C^{a_1} w^{a_2} FA^{a_3} CA^{a_4} \rho^{a_5} (w/c)^{a_6} \qquad (4)$$

From regression analyses, the values of a0, a1, a2, a3, a4, a5, and a6 are calculated and the intensity of concrete for a certain age is directly predictable. Most of the above models take into account different index properties of concrete that affect the intensity gain comportment. The analysis is a derogation and the only alternative to using other index parameters is to use the intensity test outcome on a given day.

3. Methodology

The term "analysis technique" refers to a strategy for systematically solving problems. The overall research design, sampling technique, data collection process, and analysis procedure are all part of it. It is often carried out after the researcher has obtained some insight into the topic by secondary study or analysis of previously collected primary data.

A) Data Collection :

This dataset is collected from UCI Machine Learning Repository. The dataset includes the number of instances (observations) is 1030, the number of attributes is 9 (8 quantitative input variables, and 1 quantitative output variable). A power forecast from the data available is a very unpredictable process. Thus, the pressure force of concrete depends on the following eight input characteristics in this approach:

$1.Cement(kg/m^3)$
$2.Fly\_ash((kg/m^3)$
$3.Blast\_furnace\_Slag(kg/m^3)$
$4.Water(kg/m^3)$
$5.Superplasticizer(kg/m^3)$
$6.Coarse\_aggregate(kg/m^3)$
$7.Fine\_aggregate(kg/m^3)$
$8.Age\_of\_testing(days)$

While each aspect is defined by only one definition, the words are different ways. For instance, a block of cement may be pulverized to different degrees of finesse and made of various chemicals. The properties of concrete are affected, besides the component forms, by the mixing proportions and the mixing process. Although technical sources are experimental data documenting the thousands of possible mixes, this material has not yet been compiled by anybody. In addition, with all the important information listed a mix is nearly never described;

Table 1: Ranges of components of data sets.

Component	Minimum (kg/m^3)	Maximum (kg/m^3)	Average (kg/m^3)
Cement	71	600	232.2
Fly_ash	0	175	46.4
Blast_furnace_Slag	0	359	79.2
Water	120	228	186.4
Superplasticizer	0	20.8	3.5
Coarse_aggregate	730	1322	943.5
Fine_aggregate	486	968	819.9

B) Proposed Model:

Machine learning methods are used in the proposed scheme. To construct the model, we start with the dataset, which comprises all of the past instances and current information, and then we conduct data preprocessing (Data Preprocessing is the phase through which the data is converted, or encoded, such that the computer can easily interpret it).

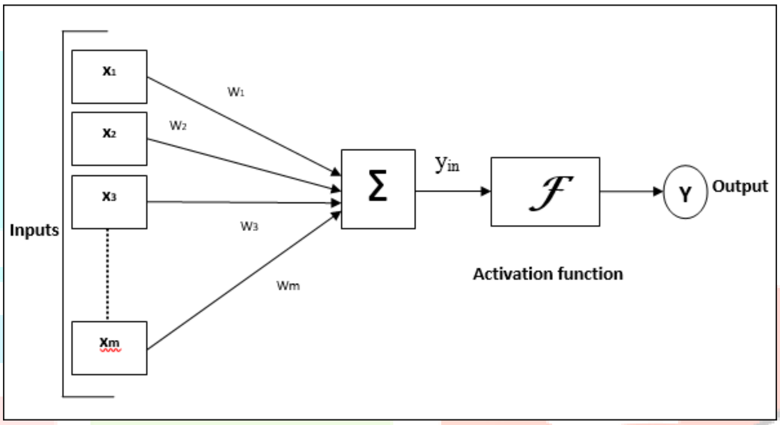

Figure 1: Proposed Model

C) Data Preprocessing:

Data processing is the process of transforming data from one medium to another that is more accessible and desirable, i.e. making it more useful and insightful. This whole method can be implemented using Machine Learning techniques, computational analysis, and analytical understanding [6]. Data preparation is a crucial step in Machine Learning because the accuracy of data and the valuable knowledge that can be obtained from it has a significant impact on our model's capacity to learn; thus, preprocessing our data until feeding it into our model is critical.

i) Handling Missing Values: There are still a few nulls values in every dataset obtained. No system can accommodate these NULL or NaN values on its own, regardless of whether it is a regression, classification, or some other form of challenge, so we must interfere. First and foremost, we must decide whether or not our dataset includes null values. The IsNull() method may be used to do this. We have several options for dealing with this problem. The simplest solution is to use dropna() to exclude all columns and rows which include missing value.

ii) Data Transformation: For our model accuracy purpose, we are using the Standard Scalar method. The standardisation (or Z-score normalisation) results in re-scaling of characteristics to ensure that perhaps the mean and the standard deviation are 0 and 1. The following is the equation:

$$x_{stand} = \frac{x - mean(x)}{standard\_deviation(x)} \qquad (5)$$

D) Data Visualization:

The pair plot represents the information to find the relationship between different factors, where the variables may be categorical or constant. Plot relationships in a dataset on a pair basis. The pair plot is used to understand the right combination of features to illustrate the interaction between two variables.

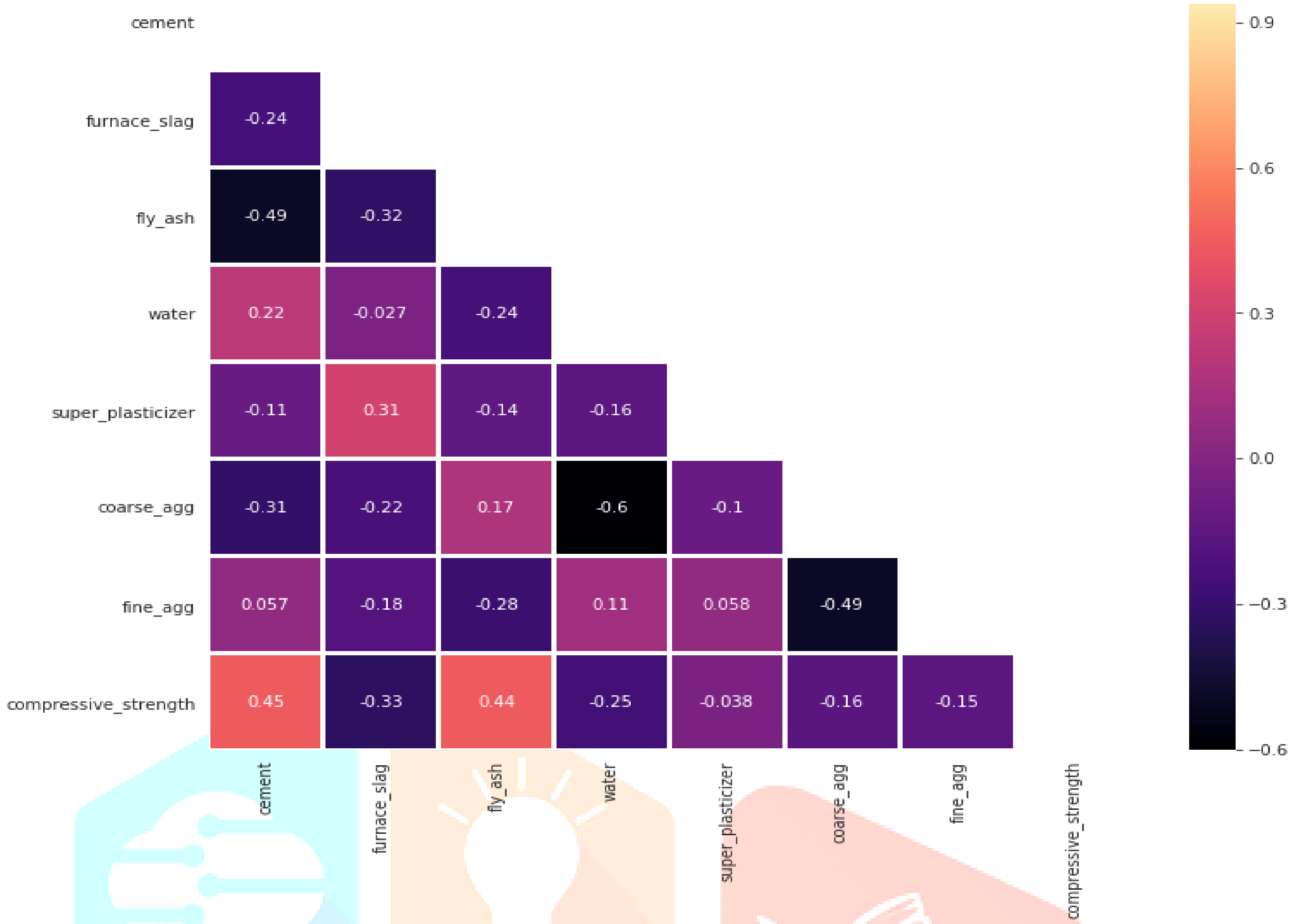

Figure 2: Correlation between 28-day compressive strength (CS) and the seven input measurement features.

A) *Tran and Test Split:*

When machine learning is being used to render decisions and predictions that were not often used to train the model, the train-test split method is used to estimate their results. It's a quick and simple procedure that allows everyone to compare the output of machine learning methods for our predictive modeling problem. The using dataset contains 1030 samples and 8 features. Therefore, the feature matrix's size is 1030x8(the rest is for labeling). Out of this feature matrix, 80% (824 instances) for the training set and the rest 20% (206 instances) for testing data are selected.

B) Algorithms:

Random Forest: The next task is to develop a classification model based on a machine learning approach and Artificial Intelligence to estimate the compressive strength. Customarily, all models rely on a feature matrix generated from the data acquired from the acquisition system. Since no thumb rule determines the choice of an algorithm for the available data to be classified, therefore several algorithms experimented with the dataset. For instance, Linear Regression, Lasso Regression, Ridge Regression, Decision Tree, Random forest, and Artificial Intelligence [7]. Among all of using six algorithms, the best two algorithms will be discussing.

1. *Random Forest:* The random forest is a classified and regression type algorithm that uses several decision trees to analyze data. When constructing each tree, it employs bagging and attributes random nature to establish a negatively correlated forest of trees whose working group estimation is more reliable than that of any single tree.

$$ni_j = w_j C_j - w_{left(j)} C_{left(j)} - w_{right(j)} C_{right(j)} \qquad (6)$$

2. *Artificial Intelligent:* The smallest neural network is the perceptron, which has n parameters, an only

neuron, but only one outcome, where n represents the number of attributes in our dataset. Forward propagation is the method of transmitting data across a neural network, and it is done in a perceptron. Multiplication the inputs value with the weights and add the results. For instance, if our row vectors of the features and weights are $x = [x_{1,} x_{2,} ...., x_n]$ and $w = [w_{1,} w_{2,} ..., w_n]$. Then their dot product should be like this.

$$\sum = x.w = (x_1 w_1 + x_2 w_2 + ... + x_n w_n) \qquad (7)$$

For moving left to right, we have to add bias b in the desired result. So the equation should be like this. These values will be store in one variable called z for further use.

$$z = x.w + b \qquad (8)$$

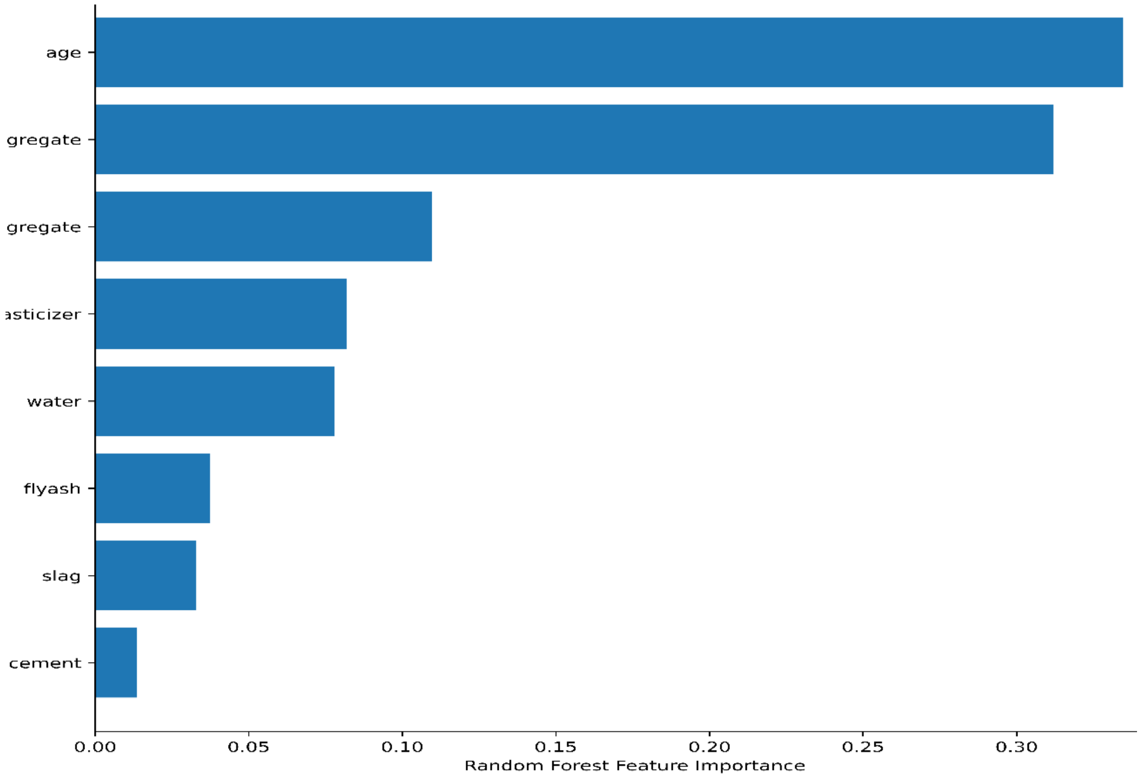

Figure 3: Features Importance by Random Forest

IV. RESULTS AND DISCUSSION

An early-day test outcome will introduce a new model to estimate compressive power. The model suggested uses standard weight concrete as its basis for the strength gain characteristics. During testing for four test outcome sets, two groups of testing data are used to build the model [8]. The four classes considered include concrete constructed from two distinct kinds of aggregates, e.g. stone aggregates and local aggregates (brick chips).

Statistical parameters such as Root Medium Square Error, Mean Average Error calculating output are used to verify the reliability of the model suggested. Table 2 and fig. 2 indicate an error of all algorithms that the value of RMSE is between 11,19 and 5,97, with the value of MAE being between 9.00 and 3.38. It can be inferred from an overall observation that all output parameters are within an appropriate range and the artificial intelligence algorithm is the best model for estimating the compressive strength of concrete.

Table 2: Eros Comparison among all algorithms

Eros	Regression Models					
	Linear Regression	**Lasso Regression**	**Ridge Regression**	**Decision Tree**	**Random Forest**	**ANN**
RMSE	10.55	11.19	10.58	6.69	5.72	**5.17**
MAE	8.44	9.00	8.44	4.26	4.25	**3.38**

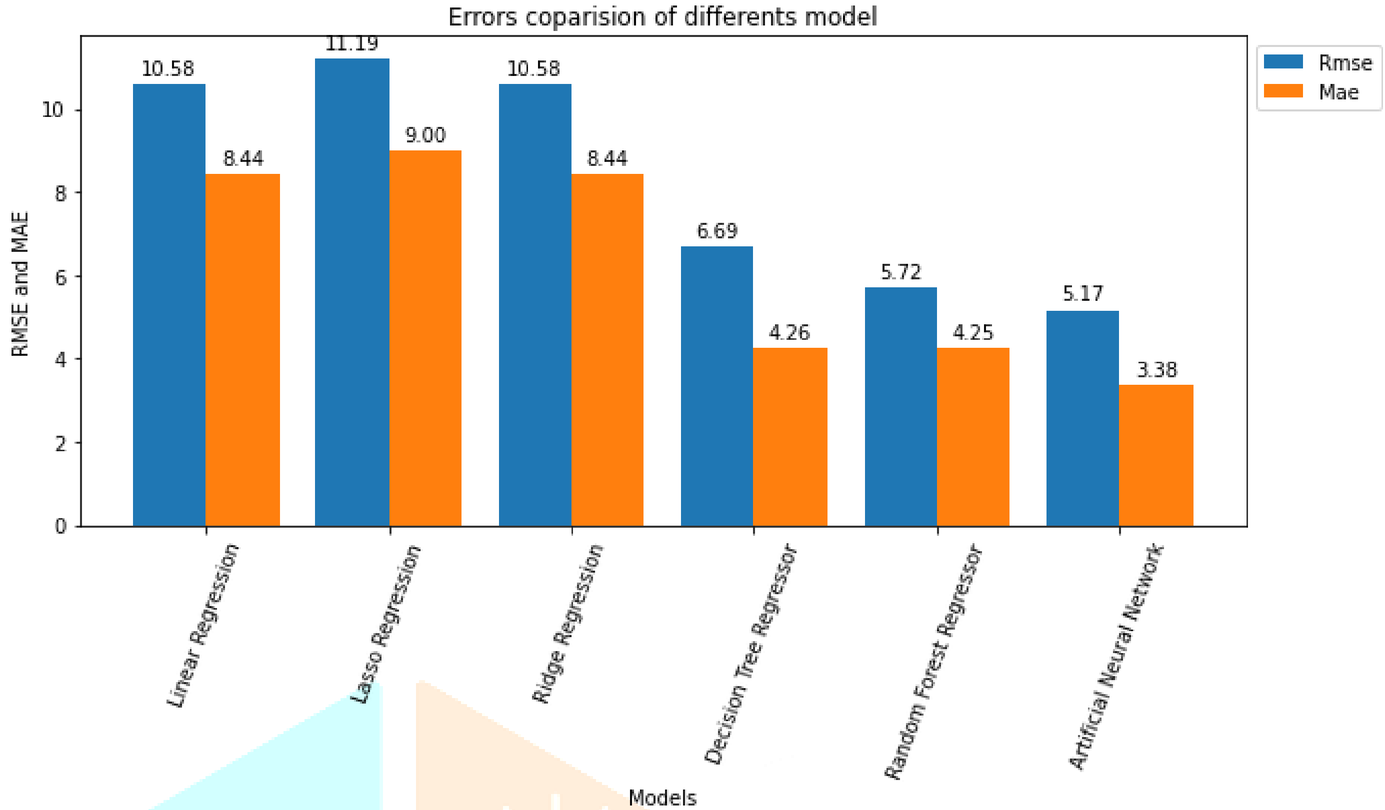

Figure 4: Variation of RMSE & MAE value for different models

V. Conclusion

This paper is a basic statistical model for predicting the concrete compressive strength from early age test data. The proposed equations will estimate intensity data for all ages. There are scopes for further analysis to assess the values of these constants without the aid of early test results whether the previous test results will approximate the two constants. This helps to decide quickly on unintended inadequate on-site concreting and to reduce the time required to implement a major civil project.

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