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Roads Cost Estimation: Comparison of the Accurateness of MLP and Linear SVR

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Abstract

Cost estimation in the early stages of construction projects is one of the crucial problems of project sustainability because costs are an integral component of any construction project contract; the completion of a project can be affected by the accuracy with which construction costs dose projected. Various machine learning algorithms were employed for estimate purposes, but neither of the techniques can be considered the best for all circumstances. This research used actual project data for rural roads in Iraq to predict the target variable actual construction cost of road structures based on machine learning techniques. For more accurate cost value two algorithms were compared: the linear support vector regression (SVR) model and Multilayer Perceptron Neural Network (MLP). The highest accuracy has been obtained with linear SVR model. The result R2=0.999 about (100 %), and MAPE=0.00001 shows excellent predictive capabilities of the SVR, regarding that these results are for real problems from the practice. When the outcomes of the models were compared, it was discovered that forecasting with SVR was much more accurate.

Keywords: Construction, Roads, Cost estimation, Machine learning, Linear SVR

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تقدير تكلفة الطرق: مقارنة دقة MLP وSVR الخطي

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الخلاصة

تقدير التكلفة في المراحل الأولى من مشاريع البناء هو أحد المشاكل الحاسمة لاستدامة المشروع لأن التكاليف جزء لا يتجزأ من أي عقد مشروع بناء يمكن أن يتأثر إكمال المشروع بالدقة التي يتم بها تقدير تكاليف البناء. تم استخدام خوارزميات مختلفة للتعلم الآلي لأغراض التقدير ولكن لا يمكن اعتبار أي من التقنيات الأفضل لجميع الظروف. استخدم هذا البحث بيانات المشروع الفعلية للطرق الريفية في العراق للتنبؤ بتكلفة البناء الفعلية المتغيرة المستهدفة لهياكل الطرق بناءً على تقنيات التعلم الآلي. للحصول على قيمة تكلفة أكثر دقة تمت مقارنة خوارزميتين: نموذج الانحدار المتجه للدعم الخطي (SVR) والشبكة العصبية متعددة الطبقات Perceptron (MLP). تم الحصول على أعلى دقة مع نموذج SVR الخطي. النتيجة R2 = 0.999 حوالي (100٪) و MAPE = 0.00001 تُظهر قدرات تنبؤية ممتازة لـ SVR فيما يتعلق بأن هذه النتائج لمشاكل حقيقية من الممارسة. عندما تمت مقارنة نتائج النماذج تم اكتشاف أن التنبؤ باستخدام SVR كان أكثر دقة.

الكلمات المفتاحية: البناء، الطرق، تقدير التكلفة، التعلم الآلي، SVR الخطي

Introduction

Early-stage cost projection is a critical problem in a project's life cycle. Construction project cost is one of the main contract data, and poorly assessed and contracted cost might incur additional expenditures during project implementation.[1]The cost of construction is determined by various factors, including the project's location, kind, duration, and schedule, amount of recycling or building materials, labor, equipment, and method. Early cost estimating leads to cost reductions, resulting in a more sustainable project.[2]

Project information, historical data, existing data, estimating methodology, cost estimator, and estimates are all part of the anticipating process. [3]

For conceptual estimation of construction costs, cost models are a viable alternative. Because of this, developing a cost model can be difficult, as many factors contribute to project costs. In addition, cost variations are caused by changes in economic variables and indexes, particularly in a volatile or unstable economic environment. These changes have the potential to increase or decrease building costs, are difficult to predict and are frequently overlooked in standard cost estimates. These changes can raise or lower building costs, are difficult to estimate, and are typically overlooked in traditional cost prediction calculations [4].

Modern computer technology has been used to solve numerous construction issues in different domains of civil engineering [5]. With the expansion in the human population, the effectiveness of the static technique is compromised by a high rate of false positives or negatives, and the project takes a considerable amount of time to complete [6] .Recently years, Machine learning technique proposed for solving problems, and it enables to finding an optimal solution for complex problems[7]. Experience has demonstrated that there are frequently disparities between estimated and realized building costs, and that these inconsistencies are caused by a lack of data and knowledge in the conceptual phase [8].

Predicting costs at the beginning of a project is difficult. Thus, many researchers have thought about this issue in an effort to develop a more precise forecasting model. Numerous approaches and strategies have been employed in the field of modeling. Neither method might be regarded optimal in every situation. It is suggested to evaluate the efficacy of multiple approaches used in a given scenario and to settle on the most precise model. Therefore, the idea and the main objective of this research are to investigate two models to develop a model with the best accuracy for considered experimental data. In this research, actual data for road structure projects has been considered. The rest of the manuscript is divided into mentioning the related works, describing the methods used in this research; machine learning prediction models for construction project costs the training and testing model; the results and discussion; and finally, the conclusions.

Related works

Several studies on construction cost estimation using machine learning, neural network, regression, or stochastic techniques have been published in the last two decades.

Neural Networks, Linear Regression, and Autoregressive Time Series are utilized to estimate the Construction Cost Index for concrete structures based on records of essential construction costs proposed by Elfahham [11]; the dataset has been used was 16 years (the year 2002–2018) for a yearly basis to provide a clear picture of economic changes each year for prices of structural steel, Portland cement, bricks, sand, and gravel as essential cost items.

The predictive capabilities of six different machine learning algorithms—linear regression, artificial neural network, random forest, extreme gradient boosting, light gradient boosting, and natural gradient boosting—have been compared by Chakraborty et al. [12] dataset representing six different structural assemblies (one-and two-way slabs; flat plates with & without drop panels, multi-span joist slabs; and waffle slabs) was utilized, but this data was not for real projects. Hakami et al. demonstrated that ANN outperformed the traditional method in Yemen with (MAPE = 0.1). [13] with a dataset of 136 implemented projects

ANN has also been used for the dataset containing 124 road projects data, Transport infrastructure projects (Road) of the Gujarat Region by Suneja et al. [14] The author concentrated on the cost of road infrastructure projects in the early stages before construction. The (RMSE and MAPE reached 274.40 and 70.3%, respectively).

Peško et al.[16]used artificial intelligence for the estimation of cost and duration in construction projects to accomplish more precision. Both MLP (Multi-layer Perceptron) and RBF (Radial Basis Function) models were used to deal with classification problems, with MLP models dealing with regression problems and RBF models dealing with clustering problems. The dataset was 166 projects for urban roads (construction work and/or reconstruction). The input parameters for constructing the model for the work on roadway construction and landscaping.

None of the aforementioned techniques can be regarded as the absolute best. It is therefore envisaged that the research would shift towards a comparison of various modeling methodologies, neural networks, supporting vectors, etc. The objective of this study is to compare several forecasting strategies in order to determine which method best fits actual data.

Road Construction Dataset

The first study phase was to designate a sufficient experimental database as shown in figure 1. An effort was made to obtain the dataset that complies with the methods that were used in our study dedicated to predict road construction costs. About 3000 projects of road constructions in rural areas in Diyala governorate were collected for the period from 2012 to 2021. These projects included many types of projects such as; new road construction, construction of asphalt pavement layers only, asphalt overlay, and pavement maintenance. After conducting a screening process to these projects, only those whose construction items were chosen to be taken under consideration in this research while excluding all the others. The final screening produced some 1659 project that encompasses at least one construction item, every project has 24 features and that is our dataset as shown in table 1.

Table 1: Road construction dataset

Feature No.	Project data	Data Description	Data type	measurement Unit
Data for the construction items group				
1	Natural Ground Preparations	Natural ground preparations price	Numerical	Iraqi dinar
2	Earthwork Layers	Earthwork embankment price	Numerical	Iraqi dinar
3	Granular Sub-Base Layer	Granular sub-base layer price	Numerical	Iraqi dinar
4	Asphalt Concrete Base Layer	Asphalt concrete base layer price	Numerical	Iraqi dinar
5	Pipe Tunnel 60cm	Pipe tunnel installation works price	Numerical	Iraqi dinar
6	Granular Shoulder Layer	Granular shoulder works price	Numerical	Iraqi dinar
Economic attributes group				
1	GDP	Iraq Gross Domestic Production per capita	Numerical	N/A
2	Unemployment Index	Iraq Unemployment Rate	Numerical	%
3	Inflation Index	Iraq Inflation Rate	Numerical	%
4	Oil Price	Crude oil price	Numerical	$
5	Dollar Exchange Rate	Dollar change	Numerical	$
6	Year	Year of execution	Numerical	N/A

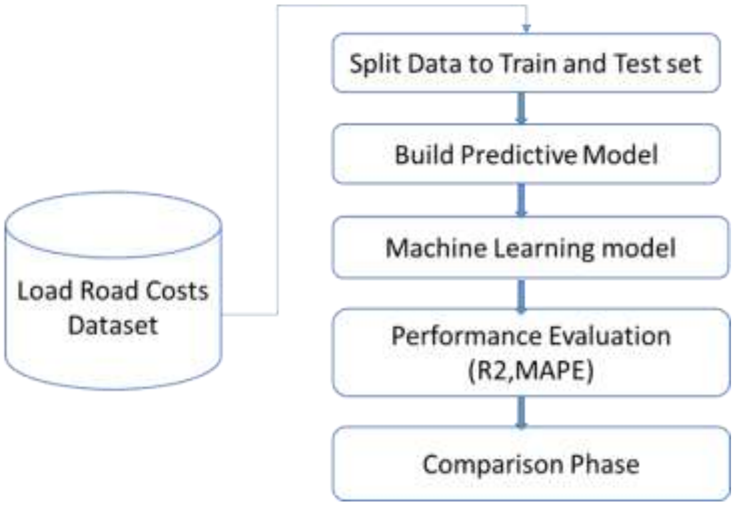

Figure 1: Framework Machine Learning Models for road cost prediction

Methods

AI is used to estimate or compute the cost of construction-based materials or construction datasets. Generally, the machine learning (ML) technique is a main field within AI that is utilized to accurately forecast classes or targets. ML is divided into superior and inferior approaches[9].

Machine learning, which examines this process in automated systems, is only one subfield of data science. Decision-making systems can be trained with data, and this training process is ongoing so that the system can update its knowledge and get better at making decisions. Recent scientific advances may explain ML's importance. Civil Engineering is a discipline that considerably benefits from recent technical breakthroughs in data collection [9].

Machine Learning prediction models for construction project costs

Machine learning algorithms make it possible to create more intricate cost prediction models. Instead of using completely static prediction models comparable to those that are utilized in time series analysis, they learn from the variables that are input and produce predictions on output variables that are influenced by the data. In addition, the use of explanatory variables, which are often referred to as features in the context of machine learning, enhances a machine learning model's ability to recognize variation and makes for a more precise prediction [10][11]. A parallel processing network, an artificial neural network structures the nonlinear relationship between response and explanatory variables. The Multilayer Perceptron is a feed-forward artificial neural network with three layers: the input layer, the hidden layer, and the output layer. MLP neural networks modify the weight proportionally to the difference between the desired output and the projected output using backpropagation. The collection of training data for the SVR model contains both independent variables and observed dependent variables. The objective of the SVR model is to determine the predicted function from the observed function with minimal error and excellent generalizability. In this research, these two machine learning methods are compared in order to link the overall construction cost of the roads in the study area to a set of explanatory variables for the establishment of cost prediction models. They will briefly summarize the approaches in the following sections

Linear Support Vector Regression (SVR)

SVR is a frequently utilized regression technique derived from support vector classification (SVC) and expands least-square regression by taking into account a ϵ-insensitive loss function. The kernel technique using in non-linear svr, which translates data to greater dimensional space and applies a kernel function, is frequently employed with both SVR and SVC. The standard kernel functions are Linear, Gaussian kernel otherwise called Radial Basis Function (RBF) kernel, and Polynomial kernel.

Moreover, the idea of regularization is commonly employed to prevent overfitting the training data [12]. As a result, an SVR solves an optimization problem involving two parameters: the regularization parameter (C). C term is trade off the complexity, it determines the tradeoff between the model flatness and empirical risk. As shown in algorithm 1, as well as the error sensitivity parameter (commonly termed ϵ). The solution for optimization problem is given as in Equation (1)

$$f(x) = \sum_{i=1}^{n_{sv}} (\alpha_i, \alpha_i^*) K(x_i, x) \quad (1)$$

$$subject\ to : 0 \leq \alpha_i^* \leq C, 0 \leq \alpha_i \leq C$$

Where $n_{sv}$the number of support is vectors and $K(x_i, x)$is a kernel function [13].

Given a set of training instance-target pairs $\{(x_i, y_i)\}, x_i \in \boldsymbol{R}^n, y_i \in \boldsymbol{R}, i = 1, \ldots, l$, linear SVR discovers a model w such that $\boldsymbol{w}^T \boldsymbol{x}_i$ is close to the target value y_i.

In linear SVR, rather than a line or hyperplane, there is a -tube with a regression line in its center. This tube has a width of Epsilon, and the width as measured by Bush is along the axis, not perpendicular to the tube, but vertically as shown in figure 2. This tube is referred to as the ε-insensitive tube, which means that every point in the dataset that falls within the tube will have its error disregarded. Points outside the -insensitive tube determine its shape and position. Support Vectors point outside the tube and assist build the ε-insensitive tube [12].

It solves the regularized optimization problem as given below. In Equation (2), $C > 0$ is the regularization parameter

$$min_w\ f(w), where\ f(w) \equiv \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_\varepsilon(w; x_i, y_i) \ldots \ldots (2)$$

And

$$\xi_\varepsilon(w; x_i, y_i) = max(|w^T x_i - y_i| - \varepsilon, 0) \ldots \ldots (3)$$

Or

$$max(|w^T x_i - y_i| - \varepsilon, 0)^2 \ldots \ldots (3)$$

Where is the $\varepsilon - insensitive$ loss function related with(x_i, y_i). The parameter ε is provided such that the loss is zero if $|w^T x_i - y_i| \leq \varepsilon$ [12]. SVR utilizing (2) and (2) is L1-loss and L2-loss SVR, accordingly. The L1 Loss Function is used to find the optimal loss function for minimizing the error, which is defined as the sum of all the absolute discrepancies between the actual and predicted values. When trying to forecast a value, the L2 Loss Function is used to minimize the error, which is the total of all the squared discrepancies between the actual and anticipated values. L1 loss is not distinguishable, but L2 loss is distinguishable. It is rather not twice distinguishable and is well recognized. A bias term b is utilized in standard SVC as well as SVR to make the prediction function $w^T x + b$ [12].

Algorithm 1: Training linear SVR

Require:X $and\ y$ loaded with training labeled data, $\alpha \Leftarrow 0\ or\ \alpha \Leftarrow partially\ trained\ SVR$

1: $C \Leftarrow some\ value\ (10\ for\ example)$

2: **repeat**

3: **for all** $\{x_i, y_i\}, \{x_j, y_j\}$ $\boldsymbol{do}$

4: Optimize α_i and α_j

5: **end for**

6: until no changes in α or other resource constrain criteria met

Ensure: Retain only the support vectors ($\alpha_i > 0$)

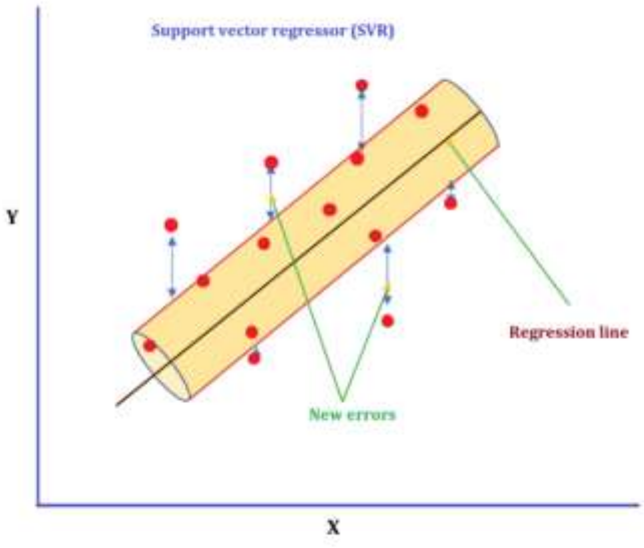

Figure 2: Linear Support Vector Regression

Multi-Layer Perceptron Neural Network (MLP)

The initial processing elements in MLP are prepared in a one-directional form. Information develops in these networks through interactions across three kinds of matching levels: output, hidden, and input layers. Activation and summation functions are two functions that may be performed on each MLP node. For example, the summation function stated in Eq. 4 used to obtain the product of input values, weight values, and bias values [14].

$$S_j = \sum_{i=1}^{n} \omega_{ij} I_i + \beta_j \quad (4)$$

in which n resembles the total number of inputs, w_{ij} refers to the connection weight, β_j expresses a bias value, as well as I_i resembles the input variable$i$,. Following that, an activation function is engaged relying on the Eq. 11's result. The MLP may be activated in a combination of ways, the most familiar of which is the S-shaped sigmoid function, as per research [15]. Eq. 5 may be utilized to calculate this function [16].

$$f_j(x) = \frac{1}{1+e^{-S_j}} \quad (5)$$

Consequently, the final output of the neuron j is attained using Eq. (6):[16]

$$y_i = f_i\left(\sum_{i=1}^{n} \omega_{ij} I_i + \beta_j\right) \quad (6)$$

Algorithm 2: Training MLP
1: choose an initial weight vector $\sim\omega$
2: initialize minimization approach
3: **While** error did not converge **do**
4: **for** all $(\sim x, \sim d) \in D$ **do**
5: apply $\sim x$ to network and calculate the network output
6: Calculate $\partial e(\sim x)$

7: **end for**

8: Calculate $\partial E(D)$

9: for all weights summing over all training patterns

10: Perform one update step of the minimization approach

11: **end While**

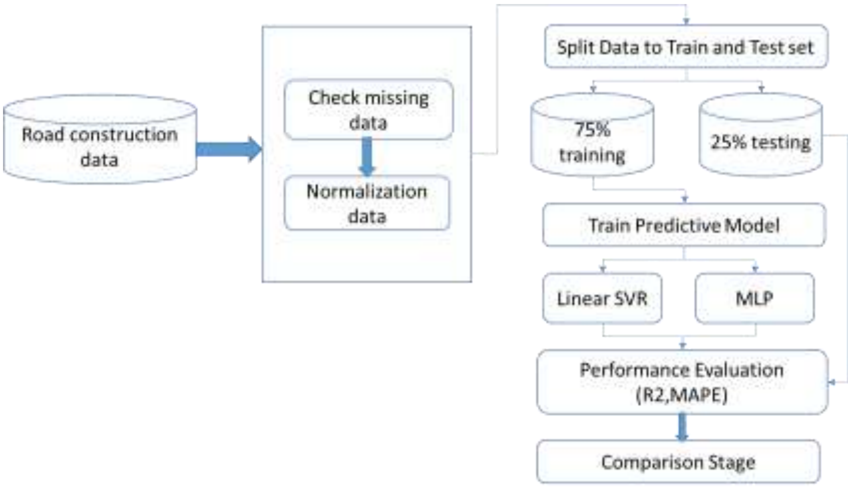

Figure 3: Design of the proposed system

Proposed System

The prediction system has four stages executed sequentially, starting with reading the dataset ends with performance evaluation, figure 3 displays the design of the proposed system. Raw information was obtained from a legitimate government source and manually entered into an excel file, which was then prepared for use in the proposed project cost prediction model. There is no need for any compensatory approaches because there is no missing data, and no require compensating methods because there are no missing data following verification Applying the formula below, the datasets were normalized between 0 and 1, given the varying ranges of the variables.

$$\acute{x}_i = \frac{x_i - min_d}{max_d - min_d}(max_n - min_n) + min_n \text{ .... (7)}$$

Assume that $minA$ is the minimum value for attribute A and $maxA$ is the maximum value for attribute A. Min-max normalization maps a value x_i of A to $\acute{x}_i$ in the range [max_n , min_n].

Min-max normalization relates to a linear modification of the main data and keeps the correlations between the original data values [17]. For model training and testing, it Split the dataset into random train and test subsets, by using python library sklearn and the module (model selection) the class (train test split) with the parameters test size, train size and random state. Figure 3 displays the design of the proposed system.

In this study test and train size was used defaults value, so the data used for training was 1243 samples (75%) as the data used to test the model was 415 samples (25%) from a total of 1659 samples as shown in table 1. Random state parameter has been passed an integer number (3) for reproducible output across multiple function calls. In the testing phase, the two supervised machine learning algorithms are used to identify effective and efficient prediction models for road costs. Several models of these algorithms are presented, and the turning and training parameters of each algorithm are investigated in order to produce the best possible prediction results.

In this study, it was tested the performance of the ANN model by choosing different type for solver parameter shown in table 3. For the linear SVR model, it was tested the efficiency of parameter max_iter for different values as shown in table 4.

Only if the majority of the items in a ground truth group are accurately predicted can the coefficient of determination and the mean absolute percentage error provide a good score (MAPE), these evaluation metrics were used in this research [23] are calculates as follows:

$$R^2 = 1 - \left(\frac{SSE}{SST}\right) \text{ .... (8)}$$

Where SSE is the sum of squares of the residuals and SST is the total sum of squares. (Worst value = $-\infty$; Best value = $+1$)

If x denotes the vector of explanatory variables (the input to the regression model), y denotes the target variable and g is regression model, the MAPE of g is obtained by averaging the ratio over the data[18].

$$\text{MAPE} = \frac{|g(x) - y|}{|y|} \quad \text{.......} (9)$$

Table 2: The number of training and testing data

dataset	Training set	Testing set
1659 samples	1243 samples	415 samples

Table 3: Performance evaluation results for the MLP algorithm.

Model setting	$\mathbf{R^2}$	**MAPE**	Time 1	Time 2
Solver = ‘lbfgs’	0.80	3.56	3.8	3.8
Solver = ‘sgd’	0.95	0.005	0.09	0.09
solver= ‘adam’	0.91	1.22	1.8	1.8

Table 4: Performance evaluation results for the linear SVR algorithm

Model setting	$\mathbf{R^2}$	**MAPE**	Time 1	Time 2
max_iter = 1000	0.92	0.21	0.02	0.002
max_iter = 500	0.99	0.00001	0.01	0.000
max_iter = 100	0.90	1.23	0.02	0.003
max_iter = 10000	0.88	3.78	0.02	0.000
max_iter = 100000	0.80	5.24	0.01	0.002

Results and Discussion

A diverse set of machine learning methods has been used for reaching the optimal method for the road's construction real dataset that was proposed for the cost predictive model. This research used linear Support Vector Machines (SVM) for experiment that method on the proposed dataset, costs projected using linear SVR came in much closer to reality than expected. Figure 4 and figure 7. Depicts the good fitted regression line between the experimental values and predicted values indicating the greatest goodness of fit R2 = 0.999 with different values for max_iter parameter the good performance of the model has not changed. Table 4. Illustrate the different value for max_iter parameter and the effected on the model performance which is the highest score with the default value and when the number of iterations is higher the performance is slow. Linear SVR is shown the accurate and great model for prediction costs for road construction based on error and true points are lied exactly on one-line regression MAPE is 0.00001 as shown in figure 8, the high score for R-squared indicates the model very well fitting on the data. Such algorithms often establish a database of examples and compare new data to the database using a similarity metric in order to determine the best match and give a forecast. Multilayer Perceptron (MLP) the Artificial Neural Network method was the second method chosen for predictive modeling for construction costs. These models are based on biological neural network structure and/or function. Based on the experiment the parameter solver = 'sgd' has been used for the best result with the MLP model as shown in table 3. This method predicts costs with R2 score value is 0.95, MAPE is about 0.005. As shown in table 4. MLP model show in figure5 and figure 6. Less fitting with the data. The error ratio between the actual and expected values is greater than linear SVR depicted in Figure 9.

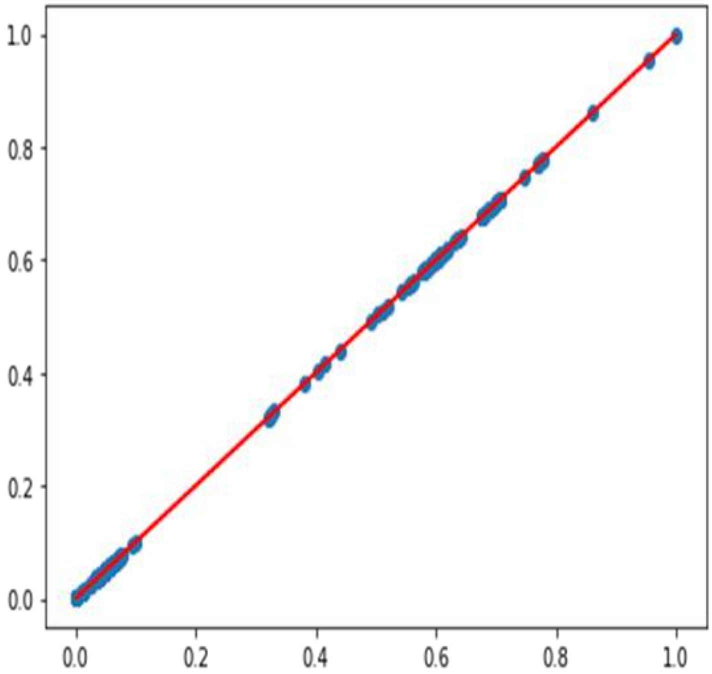

Figure 4: Overall Regression values for linear SVR Model

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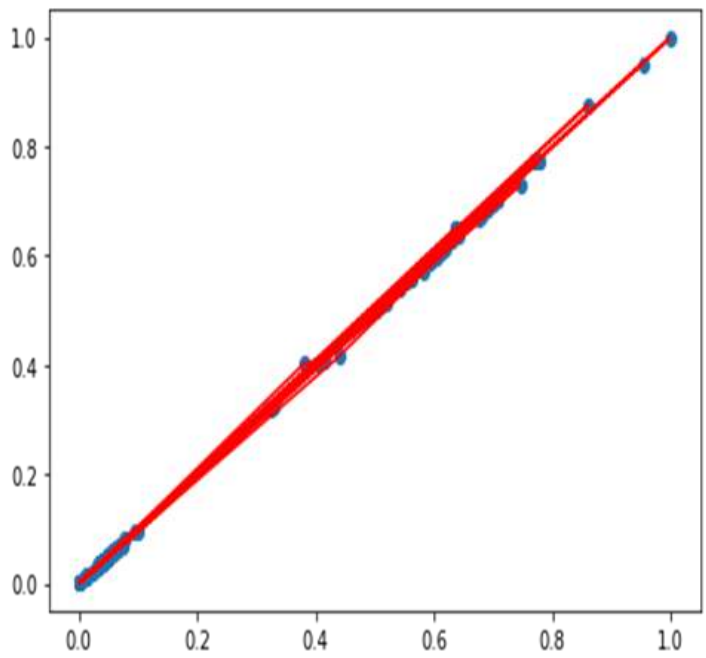

Figure 5: Overall Regression values for MLP Model

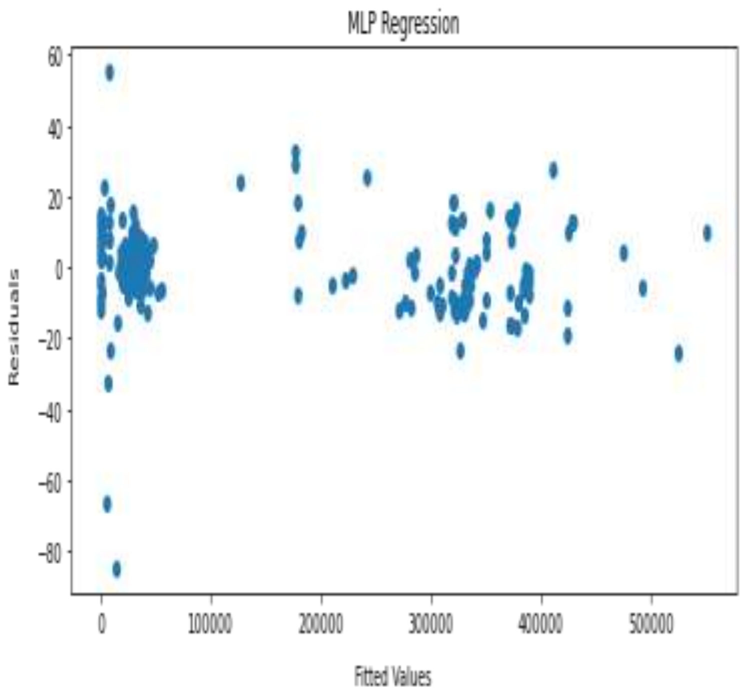

Figure 6: Fitted Values and Residuals for MLP Regression

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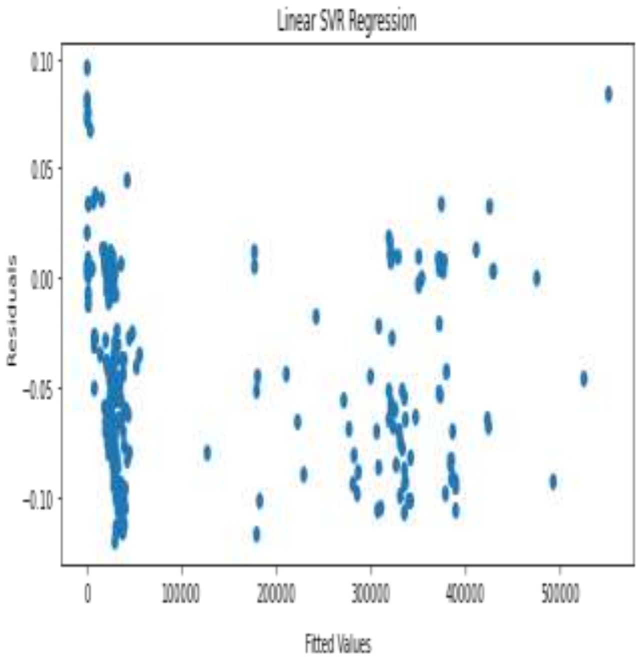

Figure 7: Fitted Values and Residuals for Linear SVR Regression

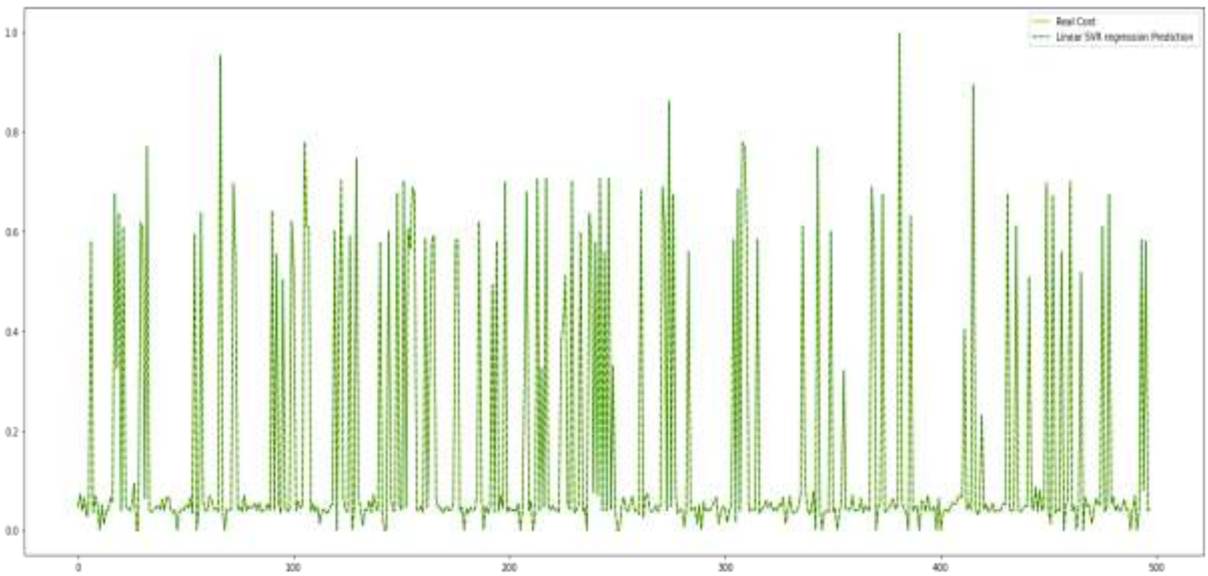

Figure 8: Experimental data and predicted data using linear SVR

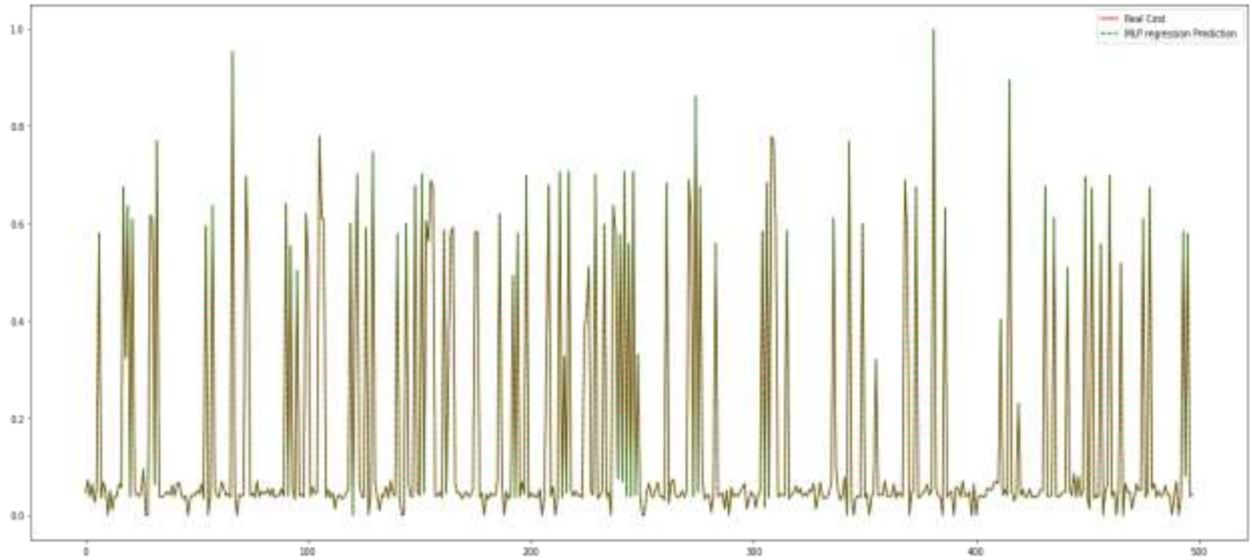

Figure 9: Experimental data and predicted data using MLP

Table 5: Estimation of the accurateness for testing data for Linear SVR Model

COEFFICIENT OF DETERMINATION R2 = 0.99999 (99.999%) MAPE = 0.000001

Table 6: Estimation of the accurateness for testing data MLP Model

COEFFICIENT OF DETERMINATION R2 = 0.957762 (95.776%) MAPE = 0.005

Conclusions

Road engineers have expend a great deal of time and effort on the task of cost estimating for road construction. Additionally, Cost forecasting accuracy can have a significant impact on the construction process and on the businesses of project participants. Cost forecasting is therefore a particularly challenging and responsible process. Learning from the costs of previous projects is a critical consideration. For that purpose, a dataset for the costs of the previously realized road projects was formed. Data were used for creating models for predicting road costs using linear support vector regression (SVR) and Multilayer Perceptron Neural Network (MLP).

With the linear SVR model we received a particularly more accurate estimation. The result R2=0.999 about (100 %), and MAPE=0.00001 shows excellent predictive capabilities of the SVR, regarding that these results are for real problems from the practice.

The models are useful for predicting building costs quickly and efficiently, but they are not a replacement for detailed cost estimation. As a result, they are appropriate for project participants and clients throughout the first phase of construction projects.

The restriction of these models is that they can only be used in road projects where there is no major influence of physical elements.

Nonetheless, the findings of this study provide a solid foundation for further research using alternative machine learning or deep learning techniques and larger datasets. Furthermore, the methods used could be used to construct alternative models for predicting road costs in the future.

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