Predicting construction productivity with machine learning approaches

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Abstract –
Machine learning (ML) is a purpose technology already starting to transform the global economy and has the potential to transform the construction industry with the use of data-driven solutions to improve the way projects are delivered. Unrealistic productivity predictions cause increased delivery cost and time. This study shows the application of supervised ML algorithms on a database including 1,977 productivity measures that were used to train, test, and validate the approach. Deep neural network (DNN), k-nearest neighbours (KNN), support vector machine (SVM), logistic regression, and Bayesian networks are used for predicting productivity by using a subjective measure (compatibility of personality), together with external and site conditions and other workforce characteristics. A case study of a masonry project is discussed to analyse and predict task productivity.

Keywords –
Machine learning; Labour productivity; Construction; Crew management

1. Introduction

There are numerous factors that impact task productivity of construction crews such as external conditions, site conditions, and workers characteristics. The interrelationships between the factors and the factors' effects need to be considered by site managers when planning work to better predict task productivity and determine which factors will have a negative impact, so that they can take actions such as identifying which workers will be part of a crew, determining optimal crew size, and allocating workers and crews to the proper tasks. Existing modeling approches have not considered a subjective and essential characteristic of the workforce (compatibilty of personality) and the interrelationships between workforce characteristics, site and external conditions to accurately predict task productivity of construction crews. Therefore, a model to better understand the interactions between the factors and their combined effects to better predict task productivity needs to be developed. Additionally, the developed models make predictions without considering various levels of productivity that are useful for planning future work and establishing acceptable levels of production. In this work, levels of productivity are classified in 3 classes (high, medium and low) and the class definition was based on the number of standard deviations from the empirical mean productivity.

2. Machine learning in construction

Machine learning (ML) as a major area of interest within the field of artificial intelligence (AI) has been applied to construction and the built environment research for more than two decades [3], [5-7]. Supervised learning, including logistic regression, support vector machine (SVM), and random forest among others, are the most widely used type of ML algorithms in the construction field. Supervised learning is a ML method that learns a function that maps the input to output based on example input-output pairs and infers a function from labelled training data consisting of a set of training examples [10]. In most construction applications, supervised learning is used for data classification [8]. Unsupervised learning that focuses on data reduction and clustering problems is a method of machine learning. No pre-labelled training examples are given, and the input data is automatically classified or grouped [9-10]. Because in the construction industry the unlabelled data has many limitations, relatively speaking, the information that can be extracted is less than the labelled data, so unsupervised learning is less used in the construction industry than supervised learning.

Numerous ML applications have been developed for the construction industry. Examples include supervised learning such as logistic regression [15], SVM [13,16], AdaBoost [17], Random Forest [13,18], Bayesian Network [19], and KNN [20]; unsupervised learning examples such as Principal Component Analysis (PCA) [21], and K-means [22]; Deep learning examples such as

Convolutional Neural Networks (CNNs) [23], and Recurrent Neural Networks (RNN) [24]. In the construction industry, the common experience of applying ML methods is that these models often fail when dealing with real-world problems. One possible reason is that computer engineers currently establish many ML methods, and they lack the knowledge and experience of the corresponding industry application scenarios, which leads to the existence of many errors and biases in the process of model building [7]. The challenges to the application of ML in the construction industry are threefold. Significant challenges are the lack of data, the accuracy of some ML algorithms, and the complexity of the site environment among others [8]. When dealing with these challenges, it is essential to note that it is not just about building predictive models when solving real-life construction problems. In addition to training reliable ML models, it is also necessary to consider how to integrate the experience and knowledge of construction industry experts into the model building process as a comprehensive framework [7].

ML has created new opportunities for revealing, quantifying, and understanding labour productivity in the construction process. Determining the factors that affect the productivity of construction labour is often the first step in establishing research models. The performance of these models greatly depends on the input factors. Two research gaps need to be addressed urgently. One is the identification of comprehensive factors, and the other is the weight and relationship of these factors. In identifying the factors, some studies have not considered essential factors such as subjective factors related to the workforce (compatibility of personality). In determining the relation between the factors, many studies ignore the correlation between different types of productivity factors and only consider these as independent and isolated factors or they simplify the correlation between the factors [11-13]. Future models can obtain information from real data to export behaviour or data-rules, identify critical factors, and predict productivity performance. The more fundamental factors will play a more accurate role in forecasting productivity, which requires the model to first clarify the hierarchical relationship between the factors to develop sensible strategies to better predict labour productivity. By combining ML, construction site realities, and the builder's understanding of actual engineering problems, new models can be developed to correctly represent construction scenarios.

3. Case study

To illustrate the application of ML in construction, let us consider a real-life masonry project in Atlanta, GA in the United States. The project consisted of two main buildings with an approximate area of 950,000 ft^2. Building A was mixed used space for upscale commercial stores and residential apartments. Building C had only upscale commercial stores. Up until the first storey, the floor use for both buildings were identical as well as the masonry units used. The second underground floor was used for parking, the first underground was used for storage for commercial clients, and the first floor was for commercial stores. Building A had 12 more floors of residential apartments. A data set was collected during the construction phase of this project, and it was used to determine the relationships between factors and factors' effects on task productivity. The reader is referred to [5] for an extended description of the factors.

Determining the factors that affect productivity was the first step for establishing the ML models. Various construction studies have used external conditions (temperature, humidity, wind speed, precipitation) [27, 28]); site conditions (floor level, work type, workload, complexity of task, congestion) [27,28,29]; and workers characteristics (age, experience, skill, crew size, personality [30, 31, 32], [26]). Note that there are numerous factors that affect productivity. When applying ML models, there is a game between being too narrow and too broad with the amount of information used to make predictions. If too narrow, some interrelationships might be lost and if being too broad the algorithms do not learn, and accuracy is low. In some cases, it seems that eliminating information might be more useful so that the levels of accuracy are acceptable, while allowing the models to learn from the information at hand. The best approach is often trial and error.

Productivity refers to the measure of the full utilisation of inputs to achieve an expected output [2]. In the field, productivity is measured at the task level, for practical considerations. Since masonry is one of the most labour-intensive trades in construction, the task-level model will be used in this study as single-factor productivity, which is expressed as the unit of work per labour hour [14]. To detail the factors three sections, namely, external conditions, site conditions, and workers characteristics describe typical attributes of masonry jobsites.

3.1 External conditions

The external conditions refer to the temperature regarding the building the crews were working at the specific time the data were collected. The temperature, both low and high temperature, was recorded for the day at the time the data were collected.

3.2 Conditions in masonry sites

Extensive site observations and interviews with masonry practitioners [6] were used to collect information of typical site conditions related to crews and walls. The crew size is determined by the length of the wall. A rule of thumb used by masonry practitioners is one mason for every 15-20 ft of wall [6] and it varies on site (depending on wall lengths) between one to five masons. The masonry tasks (walls) were classified in three different levels, namely: easy (difficulty = 1), normal (difficulty = 2), and difficult (difficulty = 3). This system considers crew sizes of one to five masons, but it was trained for two to three masons since it was the typical number of masons in this case study and dataset at hand.

3.3 Workers' characteristics

Masons have different ages and length of experience in the field, which could have impact on their productivity together with other external factors and conditions in the construction sites. The size of crews was annotated as it happened on site, which is typically determined by the superintendents. Compatibility between masons, defined as a measure of the capability of a group to interact and work well together to attain higher productivity [6], was collected through extensive site visits and interviews with masonry practitioners.

3.4 Dataset

The dataset of masonry work contains 1,977 data samples with 14 dimensions for training and prediction. Each of which includes the following features: low temperature of the day; high temperature of the day; level of difficulty of the masonry task; number of masons; compatibility of mason 1; compatibility (mason 1 & mason 2); compatibility (mason 1 & mason 3); compatibility (mason 2 & mason 3); age (mason 1,2&3); experience (mason 1,2&3). Productivity was measured by the number of blocks built in 5-minute time intervals. The dataset was divided into training and testing data sets and input data labelled by their corresponding productivity, which is measured by the number of blocks built per minute per mason. In the experiments, the level of productivity was classified as high (≥ 0.6), medium ($(0.2, 0.6]$), and low (< 0.2), considering that the average productivity of the whole data set is 0.433 and the standard deviation is 0.182. To ensure the input data was internally consistent, standardisation was implemented using Scikit-learn to pre-process the data. The dataset was balanced so that each class had approximately the same amount of data samples. To prevent the trained model from overfitting on certain classes while underfitting on other classes, enough duplication of the data in the minority classes were added to the dataset. Then, the dataset was shuffled and divided into training, validation and testing sets in the ratio 2400:700:711. Further details of data processing can be found in [5].

3.5 Experiments

KNN [8] is a simple, supervised machine learning algorithm that can be used to solve both classification and regression problems. KNN classifier determines the class of a data point by majority voting principle. For example, if K is set to 5, the classes of 5 closest points are checked, and the prediction is done according to the majority class. To determine how close between the data points, Euclidean distance is one of the most used distance measurements. In this case, a KNN model where K = 10 is built using the Scikit-learn library and achieved the classification accuracy of 97.5% with grid search method. Different values of K have been explored and when K = 10, the model achieves the highest accuracy. The confusion matrix is plotted in Figure 1.

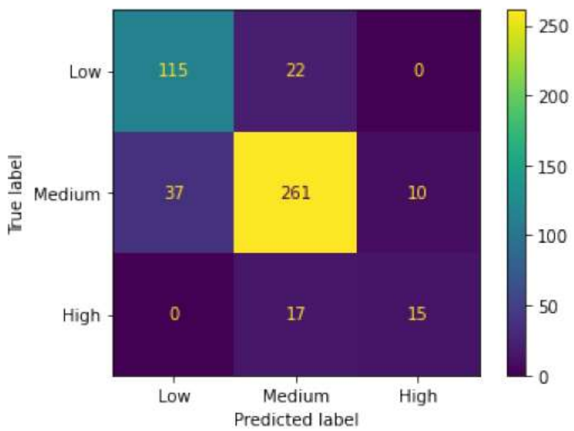

Figure 1. Confusion matrix of KNN

A logistic regression model is built using the Scikit-learn library and Liblinear [2] and achieved the classification accuracy of 85.2%. Logistic regression [3] is a statistical learning technique categorised in supervised machine learning methods for classification tasks. Logistic regression uses the sigmoid function 2, which takes any real value between zero and one. The logistic regression algorithm becomes a classification technique only when a decision threshold (default = 0.5) is brought into the picture.

A DNN is a deep learning model that is focused on emulating the learning approach that humans use to gain certain types of knowledge. Like biological neurons, which are present in the brain, DNN also contains several artificial neurons, and uses them to identify and store information, then transform the input into classification or regression results. In the experiments, rectified linear unit (ReLU) was chosen as it is commonly used and has a well-performing activation function. In the output layer, log softmax was chosen to predict the class of the productivity level. Cross entropy loss was selected as the loss function with a two-layer architecture (14-8-3), that is, there are 14 neurons in the input layer, 8 in the hidden layer and 3 in the output layer, and a three-layer architecture (14-10-5-3). Then, the trained model was tested on the testing dataset. The best classification accuracy obtained, after probing with different architectures was 97.5%. A Support vector machine (SVM) [26] is a machine learning technique to find a hyperplane in an N-dimensional space (N – the number of features) that distinctly classifies the data points. In this task, SVM classifiers with Sigmoid kernels as expressed by the formula stated in (1):

$$K(X,Y) = \tanh(\gamma . X^T Y + \gamma) \tag{1}$$

These were deployed to classify the level of productivity and the result, and the accuracy obtained was 95.8%. A Bayesian network is a type of the probabilistic graphical modelling technique that is used to compute uncertainties by using the concept of probability. Bayesian networks can take an observed event and forecast the likelihood that any of numerous known causes played a role. In this task, a Bayesian network was developed to classify the level of productivity and the accuracy obtained was 81.2%.

The confusion matrix is a performance measurement for ML classification problems to check the performance of a classification model on a set of test data for which the true values are known. The column represents the ground truth of the classification, and the row stands for the predicted classification results. The confusion matrix for logistic regression is shown in Figure 2. For instance, in the prediction of the "low productivity" tasks, the KNN model correctly classified 273 of the samples, while misclassified 45 of the "low productivity" as "medium productivity."

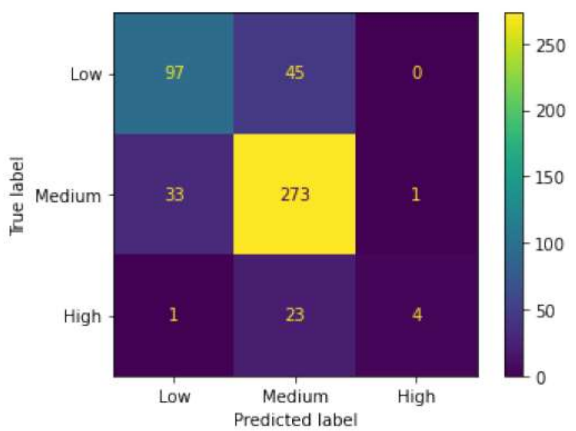

Figure 2. Confusion matrix of logistic regression

The KNN model achieved the highest accuracy (97.5%) on predicting the level of productivity of the construction project (see Table 1).

Table 1. Performance comparison of ML models

ML model	Classification accuracy	F1 Score
DNN with 2 layers	92.6%	0.903
DNN with 3 layers	88.2%	0.882
KNN (k=10)	**97.5%**	**0.986**
KNN (k=100)	81.4%	0.794
Logistic regression	85.2%	0.802
Sigmoid SVM	95.8%	0.965
Bayesian Network	81.2%	0.761

By predicting the level of productivity of the masons, the project manager can hence make decisions on how to group the masons based on their suitability and thus achieve maximum productivity and efficiency.

By removing all compatibility features (compatibility of mason1, compatibility (mason1 & mason2), compatibility (mason1 & mason3), compatibility (mason2 & mason3), the necessity of the compatibility feature could be determined. The classification results on the dataset without compatibility features are shown in Table 2. As shown in Table 2, removing the compatibility features from the input dataset results in a slight degradation on the accuracy of the classification (97.4%).

Table 2. Performance comparison of ML models (without compatibility)

ML model	Classification accuracy	F1 Score
DNN with 2 layers	91.9%	0.891
DNN with 3 layers	89.8%	0.868
KNN (k=10)	**97.4%**	**0.981**
KNN (k=100)	81.5%	0.774
Logistic regression	85.4%	0.865
Sigmoid SVM	96.0%	0.944
Bayesian Network	83.6%	0.802

Figure 3 shows the feature importance graph for KNN (k=10). The features are in order: 0=low temperature, 1=high temperature, 2= level of difficulty, 3=number of masons, 4= compatibility of mason1, 5= compatibility (mason1&mason2), 6= compatibility (mason1&mason3), 7= compatibility (mason 2&mason3), 8= age (mason 1), 9=age (mason 2), 10= age (mason 3), 11=experience (mason 1), 12= experience (mason 2), 13= experience (mason 3). As shown in Figure 3, the lowest temperature (feature 0) and highest temperature (feature 1) and the difficulty of the tasks (feature 2) have the greatest impact on predicting the productivity. Additionally, it is shown that other factors such as the experience, crew size, and compatibility play a role in the prediction power of the model.

The fact that the environmental conditions and difficulty of the task at hand prevail can be somehow explained by the fact that masonry is physically and labour intensive. Results also show that by removing compatibility gives mixed results regarding the prediction power of the model. Accuracy slightly improved in some cases (1-2%) and in other cases it was lower (1-2%). These results somehow show that compatibility might not impact productivity. However, a careful consideration in this study should be taken, as the measure for compatibility is largely subjective. In this case, there is no personality test and compatibility was determined via a subjective measure given by the foreman. While subjective, the foreman's opinion was used because it is based on the long time and careful observations of the masons and crews, she/he has managed on site. To make the metric more precise, personality tests could be done similarly to this study [25].

It might be appropriate to add here that the findings of this study contrast with [25] where it was found that personality compatibility does impact productivity and it has a positive correlation. Perhaps this is because in this study the crews were working in larger walls that were often divided by construction joints so that the foreman on site could have a better control. In the previous study [25], crews were working in residential projects that have smaller walls and crews thus required more interactions between the masons. It is interesting to look closely at the feature importance (age and wall difficulty) and how it impacts productivity. A thorough analysis of these results suggest that looking at the age of the masons might be more important to form productive teams. Perhaps pairing a young mason with a more experienced mason is better than always pairing experienced masons [6]. An additional consideration might be considering experience and compatibility depending on the type of project as well. Compatibility might be a more important factor to consider when forming crews for residential projects and easy walls, while experience might be a more important factor to consider when forming crews for commercial projects and difficult walls. These of course require further investigations.

Note that while the results might be different for other construction work, the methodology could be replicated in a similar way using ML and can be reused for projects that involve intensive labour works such as dry wall activities. Additionally, productivity measures vary depending on the type of work (structural consulting work might measure drawings per month). It might be interesting to normalise the productivity data in other activities to be able to compare with other type of works than those considered in this paper. As the definition of low or high productivity depends on the standard deviation, it will not depend on the type of work. By normalising it, it allows to classify compatibility as well and apply the methods of this study across different activities.

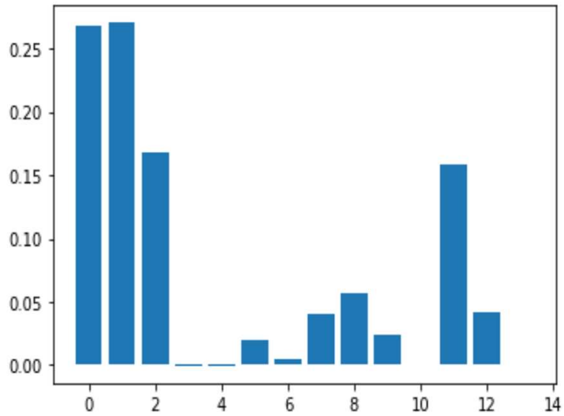

Figure 3. KNN feature importance K=10

4. Applications to optimization

Our work, and in fact any work focused on classifying and predicting productivity, can in principle be used to increase productivity. A first approach would be the following. Assume that we have a pool of N masons, from which we must select k crews of $n_1, n_2, n_3, \ldots, n_k$ masons respectively. Then, we can form an exhaustive list of all possible teams of crews of the aforementioned sizes out of the total pool of masons. When N and the $n_j's$ are small this is quite feasible. Indeed, if $N = 12$, $k = 4$ and $n_j = 3$ for all j, the total number of teams made of four crews of three masons is given by:

$$\binom{12}{3}\binom{9}{3}\binom{6}{3}=369{,}600$$

We measured the time taken by some of the algorithms we used, and once trained, the DNNs took around 0.2136 seconds to classify 697 data samples; hence, for the hypothetical example introduced above, it would take around 2 minutes to find an optimum in a single machine. The reader must consider that if the accuracy is at 85% (which is what we have now), then the probability of obtaining an optimum via this approach in the case described above is about 0.52, the colloquial toss of a coin. One way of improving these numbers is to obtain accuracies of at least 98%: in this case we would have that the probability of obtaining an optimum from exhaustive evaluation is around 0.90. Is it possible to reach these accuracy levels? Theoretically speaking, the answer is yes. For instance, in the case of DNNs by the

Universal Approximation Theorem (of course trying to avoid overfitting) and training with more data, this could be achieved or perhaps considering other factors that affect productivity, but this might have to wait some time.

Although the previous paragraph presents a simple, and perhaps obvious way of finding an optimum using classification methods in the case of larger N, say for instance N= 21, k = 7 and n_j = 3 for all j, an exhaustive approach becomes impracticable: in this case, the number of possible teams is 1.825×10^{14}. In this case, even if it only takes 10^{-6} seconds to predict the productivity of a crew, doing an exhaustive evaluation of all possible teams would take around 50,000 hours (around 5 years). Besides, if the model requires a prediction of the weather, more than 24 hours is too much to run the optimisation procedure.

Still, hope is not to be lost as something can be done. Assuming a high accuracy of prediction, we may proceed as follows: take a sample large enough but manageable and obtain an optimum from the sample. Using this approach (and to simplify our reasoning even further, assuming perfect accuracy), we can, for instance, if all we want is to get a team in the first decile of productivity, take a sample of 500 teams, and the probability of not obtaining a sample in the (real not estimated) first decile is 1.4×10^{-23}, so it is quite probable, and we could even say almost certain, that the team with the best productivity in the sample is in the real first decile of productivity. This sampling procedure gives us in turn a way to estimate the $i - th$ decile of a distribution, and in this sense estimate the highest and lowest levels of productivity of the assembled teams.

5. Limitations and conclusions

The convergence of ML into the construction management domain provides the capability to learn the highly nonlinear, complex relationships between task characteristics, site conditions, and the characteristics of workers. This study leverages the power of ML and the existing wealth of real-life scenarios in construction projects to make productivity predictions. The experiments show moderate (logistic regression and Bayesian network) to very good (DNN with 2 layers, KNN with K=10 and SVM) accuracy when using ML models to classify and predict productivity with the data collected. The models were trained with only 1,700 data points. Given that the network is relatively small compared with the total number of data points, 700 data points were used to determine the accuracy. It is unknown if the network's accuracy will improve with more data. Adding more perceptrons to the DNN can theoretically improve accuracy, but it must be done with care so that the size of the network is still small compared with the training data. If this can be successfully done, then this model can be used to plan a construction project to improve performance.

This confirms the appreciation that ML methods can be used as decision-making tools in managing crews in building construction and its use deserves to be more widely known. This can reduce the reliance on empirical estimates and computationally expensive analytical evaluations and better estimate productivity of construction crews. If these classification algorithms can be paired with some optimisation strategies as proposed in this paper, this would also confirm the appreciation that ML methods can be used as decision-making tools in managing crews in building construction, and its use deserves to be more widely known. If simple strategies for evaluating the performance of teams (groups of crews) with classification algorithms (again, we suggest using probabilistic approaches as the number of teams can be huge for exhaustive methods), this can reduce the reliance on empirical estimates and computationally expensive analytical evaluations.

There are some limitations of this study. Note that the models have not been validated yet, but we expect to do this in the future, hopefully with the support and collaboration from interested industry partners that could benefit from using the techniques developed in this study. Additionally, it would be interesting to run the experiments by removing factors to determine how much the accuracy is reduced by looking at the dynamics of the teams. For instance, determining if removing the size of the crews alongside compatibility impacts the performance of the models. These studies can also be refined using more productivity classes (in this study we used three). However, the amount of data at hand did not allow us to establish more refined productivity classes so that the algorithms would have reasonable accuracies. One of the challenges behind ML models is to obtain reliable data. We did run experiments with four classes of productivity (high, medium-high, medium-low and low) and obtained an accuracy of around 70%.

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