End-to-end GRU model for construction crew management

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Abstract. Crew management is critical towards improving construction task productivity. Traditional methods for crew management on-site are heavily dependent on the experience of site managers. This paper proposes an end-to-end Gated Recurrent Units (GRU) based framework which provides site managers a more reliable and robust method for managing crews and improving productivity. The proposed framework predicts task productivity of all possible crew combinations, within a given size, from the pool of available workers using an advanced GRU model. The model has been trained with an existing database of masonry work and was found to outperform other machine learning models. The results of the framework suggest which crew combinations have the highest predicted productivity and can be used by superintendents and project managers to improve construction task productivity and better plan future projects.

Introduction

Productivity is the main indicator of the performance in the construction industry. Performance on-site is measured through task productivity. In the field, site managers are faced with multiple factors such as external conditions, site conditions, and workers characteristics that influence task productivity of construction crews. Choosing the most productive crew is one of the most critical factors to improve construction task productivity in this labour-intensive industry. For this, site managers need to consider the factors' effect to form crews and strategically assign crews to tasks to achieve high productivity rates. Site managers however typically manage crews based on experience, which is often unreliable and time consuming. Additionally, there are multiple factors and interrelationships between factors that affect the productivity of crews (external conditions, site conditions, and workers characteristics). This complexity poses a challenge for site managers to fully understand the factors effects. Reliable and robust methods are needed to process large amounts of data to determine optimal crew formations.

Machine learning (ML) is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed (Expert.ai Team, 2020). In recent years, ML is starting to gain its significance with the potential to transform the construction industry with the use of data-based solutions to improve the way construction projects are delivered. ML techniques have been successfully applied to model and predict construction productivity (Reich, 1997; Al-Zwainy, Rasheed and Ibraheem, 2012; Mahfouz, 2012; Akinosho., 2020; Song., 2020; Cheng, Cao and Jaya Mendrofa, 2021; Florez-Perez, Song and Cortissoz, 2022). Challenges however remain. Firstly, the existing work mainly relies on the review of literature, surveys, and expert interviews (El-Gohary and Aziz, 2014; Ebrahimi, Fayek and Sumati, 2021) to identify the factors that affect productivity, with limited considerations of the complexity due to non-linearity of underlying factors, interrelationships between the factors, and temporal information and interdependencies of the data (Reich, 1997; Ebrahimi, Fayek and Sumati, 2021), Secondly, the data collected does not provide sufficient information regarding the conditions and complexity of construction sites as well as the tacit knowledge of on-site personnel. (Xu, 2021). This lack of integration of site realities and industry experts' knowledge hinders the ability to model processes in a comprehensive way (Bilal and Oyedele, 2020).

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Our previous work proposes a combined ML approach that offers a solution for classifying and predicting task productivity with experimental data of masonry tasks (Florez-Perez, Song and Cortissoz, 2022). "Compatibility" a measure of "how the masons get along" is a factor used by superintendents to form crews. This subjective characteristic (associated with the workforce) is a novel consideration for building more robust ML models to forecast construction productivity. In this work we used compatibility of personality, together with external and site conditions, and workers' characteristics (age and years of experience) to predict task productivity. K-nearest neighbour (KNN) (Batista and Monard, 2002; Delany, 2021), deep neural network (DNN) (Canziani, Paszke and Culurciello, 2016), logistic regression (Field, 2009), support vector machine (SVM) (Noble, 2006), and Residual Neural Network (ResNet18) (He, 2016; Wu, Shen and van den Hengel, 2019) alongside rigorous statistical analyses were employed to interpret data and investigate the pattern mapping between input factors and productivity class labels. Results suggest that: 1) small crews have relatively higher productivity than large crews, 2) compatibility among the masons has more significant impact on the productivity in easy but not in difficult tasks; and 3) the relevance of experience to task productivity may depend on the difficulty of the task.

Two shortcomings about our work can be stated. The data was collected in 5-minute intervals, that is, temporal sequential data. The ML models chosen however lack the capability to capture the temporal dependence in the sequential data, which leads to the loss in information and affects the performance of the ML model. Furthermore, our previous work only interprets the input data and predicts productivity with no indications of crew formation. Therefore, it is worth investigating the performance of advanced deep learning models which can solve problems with sequential input data to identify data correlations and patterns through time-series. The data at hand can be used to provide indications for superintendents to choose and assemble crews on-site.

In this article, an end-to-end GRU framework for construction project crew management is proposed to classify and predict construction task productivity from the temporal-sequential data of the existing database (external site conditions, masons' characteristics, and compatibilities). The result of the framework provides superintendents with the crew combination with the highest predicted productivity for the given task. To capture the temporal-dependency of the sequential data, variants of Recurrent Neural Network (RNN) models including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are employed to predict construction task productivity. The performance of the LSTM and GRU models are compared with the baseline models including DNN, KNN, SVM and ResNet18. The advanced deep learning models (RNN, LSTM and GRU) have achieved state-of-the-art performance. Furthermore, to help superintendents assemble the most productive crews, the end-to-end framework automatically calculates the predicted productivity of all possible crew combinations (from the available masons) and identifies the combinations with the highest predicted productivity (Bai, 2019; Hegde, 2020; Kraft, 2020). These combinations will serve as suggestions for superintendents on site, to improve productivity of construction tasks with more productive crew combinations.

Literature Review

Researchers in the construction industry have made several remarkable attempts to keep up with the pace of applying ML techniques (Akinosho, 2020). Supervised learning uses a training set to teach models to yield the desired output (Caruana and Niculescu-Mizil, 2006). Supervised learning algorithms have been extensively applied in construction including SVM, logistic regression, random forest, and KNN for supporting decision making (Wong, 2004; Akinosho, 2020), forecasting occupational accidents (Kang and Ryu, 2019), and evaluating projects (Erzaij, 2020). Unsupervised learning on the other hand uses machine learning algorithms to analyse and cluster unlabelled datasets (Marsland, 2020). Given the presence of large amounts of unlabelled data in the construction field, unsupervised machine learning algorithms such as K-means clustering and principle component analysis serve as effective tools in competitive positioning (Horta and Camanho, 2014) and sustainability evaluation (Li, 2012).

Deep learning (DL) is a subfield of ML which is based on artificial neural networks with representation learning. DL methods aim at learning feature hierarchies with features at higher levels of the hierarchy formed by the composition of lower-level features. DL has been employed to tackle construction challenges such as construction site safety (Yu, 2019), building occupancy modelling (Chen and Jiang, 2018) and energy demand prediction (Rahman, Srikumar and Smith, 2018). For the specific case of productivity, studies have benefited from the application of DL because these techniques provide an effective approach to determine the relationship between the influencing factors and productivity rates and the complexity of the combined effects between factors (Courville, 2016; Li, 2021). A noteworthy point is that many proposed approaches have been dealing with the problem of predicting productivity while ignoring the spatial-temporal dependencies of the collected dataset. In addition, many approaches generate predictions and analyse results, but do not go beyond to provide project managers and superintendents with practical tools for crew management that can support productivity improvement in real construction sites.

Construction Task Productivity

Productivity refers to the measure of the full utilization of inputs to achieve an expected output (Durdyev and Mbachu, 2011). 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 (Shehata and El-Gohary, 2011). To detail the factors three sections, namely, external conditions, site conditions, and workers characteristics describe typical attributes of masonry jobsites. The reader is referred to Florez-Perez, Song and Cortissoz (2022) for an extended description of the factors.

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. 2) Conditions in masonry sites: extensive site observations and interviews with masonry practitioners (Florez, 2017) were used to collect information of typical site conditions related to walls. The masonry tasks were classified as three different levels, namely Easy (difficulty = 1), Normal (difficulty = 2), and Difficult (difficulty = 3). 3) Workers' characteristics: masons have different ages and length of experience in the field, which could have an impact on their productivity together with other external factors and conditions in construction sites. The size of crews was annotated as it happened on site, which is typically determined by site managers in accordance with the workload. Compatibility between masons, defined as a measure of the capability of a group to interact and work well together to attain higher productivity, was collected during the extensive site visits and interviews with the site manager.

Dataset

In our previous work, a dataset of masonry work was used to analyse the factors that affect task productivity and to predict task productivity. In this study, using the same dataset, we will analyse the temporal dependency of the factors and provide site managers with indications of optimal crew formations. The dataset had 1977 data samples, 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, thus makes the dataset temporal-sequential. Therefore, LSTM and GRU models are applied to capture the temporal dependencies in the time series dataset to forecast task productivity.

Methodology

DL is a subfield of ML concerned with algorithms inspired by the structure and function of the brain called artificial neural networks. RNN is a type of artificial neural network which uses sequential data or time series data. The variants of RNN models including LSTM and GRU (Chung, 2014; Greff, 2017) were used to predict the level of productivity of construction tasks using the information from the dataset. Then, an end-to-end framework was developed to predict productivity of all possible crew combinations, from the masons available, and provide superintendents with the crew combinations with the highest predicted productivity.

Data Processing

The dataset contains 1977 data samples with 14 dimensions for training and prediction. 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 low (< 0.2), medium low ($(0.2,0.4]$), medium high ($(0.4,0.6]$), and high (≥ 0.6), 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 using the formula below:

$$X_{standardisation} = \frac{X - \bar{X}}{\sigma X} \tag{1}$$

where $\bar{X}$ and σX are the mean and standard deviation of the input dataset.

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, a sufficient amount of 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 Florez-Perez, Song and Cortissoz (2022).

Experiments

A RNN (Zaremba, Sutskever and Vinyals, 2014) is a class of artificial neural network, where connections between nodes form a directed or undirected graph along a temporal sequence. This allows the network to have memory for the earlier data points in the sequential data, to gain context and identify correlations and patterns to improve the prediction. Since our data was collected in 5-minute time intervals, the temporal dependences in this sequential dataset can be captured with the RNN networks to predict construction productivity. The original RNN model however suffers from short-term memory due to the vanishing gradient problem during back propagation (Zaremba, Sutskever and Vinyals, 2014). For this reason, LSTM and GRU can be proposed by implementation of gates, which is a memory cell to store the activation value of previous data in the long sequences. Gates are capable of learning which inputs in the sequence are important and storing their information in the memory unit. They can pass the information in long sequences and use them to make predictions. The LSTM and GRU networks differ in their structure. GRU has two gates (reset and update), while LSTM has three gates (input, output, forget). Hence, GRU is simpler than LSTM because it has a smaller number of gates. Experiments were performed with both LSTM and GRU networks, and compared with the baseline models including DNN, KNN, SVM and ResNet18 with the evaluation matrices of classification accuracy and F1 score.

For the LSTM network, a batch size of 64 was chosen which is a hyperparameter of gradient descent that controls the number of training samples to work through before the model's internal parameters are updated. Three hidden layers, with a hidden size of 32, were chosen as the structure of the LSTM model with Adam as the optimizer (Kingma and Ba, 2015) and learning rate of 0.01. To train the neural network, cross-entropy loss was selected as the loss function, which is a commonly used loss function for multi-class classification problems. The LSTM model was trained for 80 epochs until there was no significant change in the plots of training and validation loss. The best performing epoch in terms of validation loss was saved for testing the model on the testing dataset. A classification accuracy of 71.9% and an F1 score of 0.703 were achieved. The confusion matrix of the LSTM network on the testing set is shown in Figure 1. Columns represent the ground truth of the classification and rows stand for the predicted classification results.

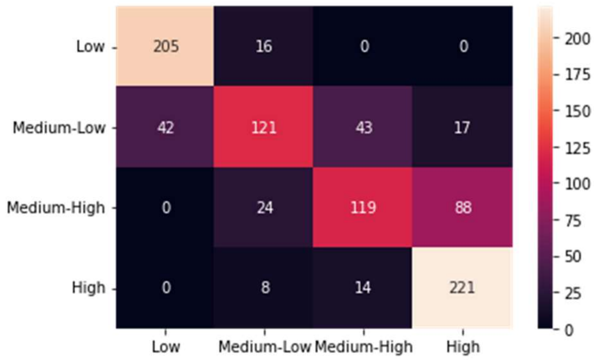

Figure 1: Confusion matrix for the LSTM network

For the GRU model, a network with three hidden layers with a size of 24 was built. A batch size of 32 was chosen together with Adam optimizer and learning rate of 0.01. The cross-entropy loss was employed as the loss function to train the GRU model for 80 epochs and the model from the epoch with lowest validation loss was saved for testing. The GRU network achieved a classification accuracy of 74.5% and an F1 score of 0.729. The confusion matrix of the GRU model on the testing dataset is shown in Figure 2.

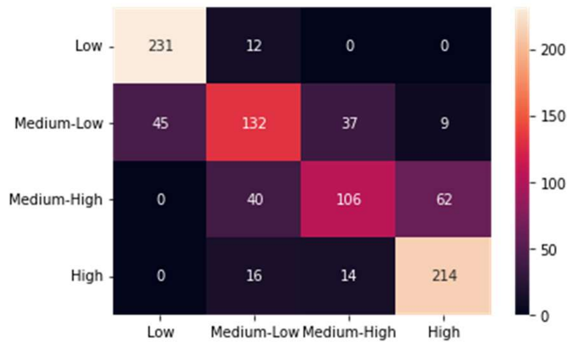

Figure 2: Confusion matrix for the GRU network

Performance Comparison

The experimental results of the LSTM and GRU models are compared with the baseline machine learning models in Florez-Perez, Song and Cortissoz (2022), which include KNN, SVM, logistic regression, DNN, and ResNet18. The comparison was made using evaluation matrices for classification accuracy and F1 scores, calculated using equations (2) and (3) below:

$$Classification\ Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{2}$$

$$F1 = \frac{TP}{TP + \frac{1}{2}(FP + FN)} \tag{3}$$

where TP, TN, FP, and FN refer to true positive, true negative, false positive and false negative, respectively. The results of the proposed methods and the baseline models on the testing dataset are shown in Table 1. Note that the highest classification accuracy and F1 scores are for the GRU model.

Table 1: Performance comparison using classification accuracy and F1 scores

Machine Learning model	Classification Accuracy	F1 Score
KNN	70.7%	0.711
Sigmoid SVM	73.7%	0.728
Logistic Regression	61.3%	0.604
DNN	67.9%	0.576
ResNet18	72.9%	0.711
LSTM	71.9%	0.703
GRU	74.5%	0.729

As shown in Table 1, the GRU model achieves the best performance in terms of both classification accuracy and F1 score, indicating that the GRU model provides the best prediction for task productivity among all experimented models.

End-to-end Framework for Crew Management

To provide superintendents with indications to assemble the most productive crews and thus maximise construction task productivity, an end-to-end framework was developed using the trained GRU network. The proposed framework can automatically calculate the predicted productivity of all possible crew combinations, with a given size from the pool of available masons and suggest superintendents which combinations which have the highest predicted productivity. The proposed framework is illustrated in Figure 3 and includes three stages, namely data collection, crew generation, and productivity prediction and ranking. In the first stage, assuming that there are n masons available to form a crew of k masons, information including external conditions, conditions in masonry sites and the workers' characteristics, including every pairwise compatibility among the masons, will need to be collected by the site manager as explained in Section 0. The compatibility of each pairwise of masons needs to be calculated. Then, for a task that requires a crew of k masons, the second stage generates all possible combinations of masons for that crew from a total number of N crews, calculated using equation (4):

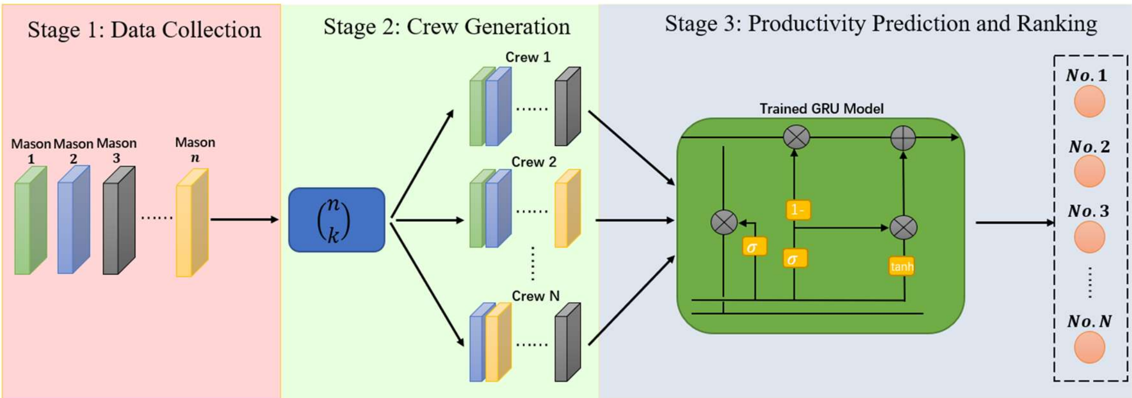

Figure 3: Pipeline of the proposed end-to-end GRU-RNN model for construction project resource management

$$N = \binom{n}{k} = \frac{n!}{k!\,(n-k)!} \tag{4}$$

Next, the information data of each possible crew is fed into the trained GRU model (discussed in Section 0), since the GRU model outperformed the baseline machine learning models and LSTM network both in terms of classification accuracy and F1 score. Given the external conditions, conditions in masonry sites and the workers' characteristics as the input data, the GRU model can be used to predict for the class of the productivity of each crew combination option and then rank the results as the output of the framework. This output provides superintendents with a simple and straightforward indication to choose the crew that maximises the productivity of the construction project.

Compared to the traditional experience-based method of choosing crews, this proposed end-to-end framework provides site managers a more reliable and robust method to improve construction productivity, as site managers may focus more on certain variables, however our model will consider all the variables affecting the productivity, making it more robust to predict the productivity. Also, this proposed framework ensures that crew management at the construction site does not only rely on the experience of superintendents, but on an autonomous system that reduces time and supports the decision-making process of crew formation.

Conclusions

This paper proposes an end-to-end GRU based method for construction crew management. The GRU is an advanced DL model, able to capture the temporal dependencies in the sequential data, to provide an accurate prediction on the class of the productivity of construction tasks. An existing real-world database of masonry work which includes external conditions, site conditions and workers' characteristics, was used to train the GRU model. This proposed GRU based framework provides a reliable and robust platform for project and site managers to efficiently select crews for different construction tasks.

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