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Integrating Deep Learning with Web-Based Price Analysis to Support Cost Estimation

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Abstract: Existing web-based cost databases have proved invaluable for construction cost estimating. These databases have been utilized to compute approximate cost estimates using assembly rates, unit rates, and etc. These web-based databases can be used independently with traditional cost estimation methods (manual methods) or used to support BIM-based cost estimating platforms. However, these databases are rigid, costly, and require a lot of manual inputs to reflect recent trends in prices or prices relative to a construction project's location. To address this gap, this study integrated deep learning techniques with web-based price analysis to develop a database that incorporates a project's location cost estimating standards and current cost trends in generating a cost estimate. The proposed method was tested in a case study project in Lagos, Nigeria. A cost estimate was successfully generated. Comparison of the experimental results with results using current industry standards showed that the proposed method achieved a 98.16% accuracy. The results showed that the proposed method was successful in generating approximate cost estimates irrespective of project's location.

Key words: Deep Learning, Building Information Modeling, Cost Estimation, Web-based Cost Databases

1. INTRODUCTION

Cost estimation can be traced back to 1785 when quantity surveying firms were first recorded [29]. Construction cost estimating is considered one of the most important and critical aspects of a construction project [28, 3]. One of the most challenging tasks for cost estimators is the generation of accurate cost estimators to aid in decision making [29]. Besides decision making, cost estimates are required for various construction management tasks such as proposal preparation, planning, organizing, directing, controlling, and evaluating [35]. According to Seeley & Winfield [29], the computation of cost estimates involves two major processes, material quantity takeoff (QTO) and the application of material unit rates. Traditional cost estimation methods are arduous, error-prone and time consuming [2]. These traditional cost estimating processes typically involves manual computations which causes time delays and additional costs [28]. Although there has been improvements on the traditional paper-based approaches of generating cost estimates, there are still limitations to the current methods/platforms for processing 2D drawings such as on-screen take-off technologies. One major limitation to these technologies is the lack of automatic change management among multiple drawing selections for take-off, making it difficult to map similar quantities proactively [26]. Building Information Modelling (BIM) has revolutionalized the way in which construction managers perform construction taks including cost estimation [10]. In utilizing BIM to generate cost estimates, quantities are generated from BIM models and unit rates/costs are assigned based on standard cost formats such as Omni- Class, UniClass, Uni Format, Master Format [10].

According to Presto [27], integrating a BIM tool directly with a costing platform can help automate the cost estimation process. Existing web-based price databases such as "RS Means" and "BCIS Online" show tremendous potential for such integration; however, these databases can only be utilized in generating approximate estimates, assembly analysis, and unit rates' analysis [3,28]. According to [2] most databases have unique coding systems for work units and resources, which could prevent successful data exchanges among users . Furthermore, another limitation to the adoption/utilzation of existing web-based price databases in the architecure, engineering and construction (AEC) industry is that these web-based price databases do not integragte the markup costs. Existing web-based price database are considered rigid, that is, these databases are not updated automatically. To address this gap, the authors propose a method that integrates deep learning techniques with web-based price analysis to support cost estimation. A few researchers have proposed methods that integrates inverse photogrammetry and BIM for automated labeling of construction site images for machine learning [7], a framework for integrated web-based price analysis to incorporate builders mark-up's decision [23]. However, these databases are rigid, costly, and require a lot of manual inputs to reflect recent trends in prices or prices relative to a construction project's location.

2. LITERATURE REVIEW

2.1. Artificial Intelligence, machine Learning, deep learning, deep learning architectures

Artificial Intelligence (AI) involves the utilization of computerized systems to perform tasks in a manner that is analogous to humans [25]. AI uses computer-processing techniques to learn, perceive, process natural languages or make human-like decisions [22].

Machine Learning (ML) is an aspect of AI that helps machines learn from data with the use of algortithms without being programmed [25]. ML evolved from AI, specifically pattern recognition and computational learning theory [25]. ML is utilized in applications for computer vision, optical character recognition (OCR), cost prediction, and etc. ML can be supervised, unsupervised, semi-supervised, or reinforced learning.

Deep learning is an aspect of ML that helps machines [17] utilize artificial neural networks and other ML algorithms to enable data to be parsed in a connected way. Deep learning can be utilized for feature extraction, transformation, and pattern analysis using supervised or unsupervised learning similar to the manner in which the human brain understands/processes data, labels, and categorizes the input received. Deep learning is an advanced approach to ML that can be utilized to distinguish and learn multiple complexity levels from large data sets [5]. Deep learning can be used to perform complex tasks on unstructured/unlabeled data unsupervised [24]. Three are typically three layer to deep learning: (1) input layer, that is the input data; (2) hidden layer, that is, the developed pattern extraction; and (3) output layer, that is, the output data. Deep learning processes are iterative, an output layer from a deep learning model can be utilized as an input layer for another deep learning model. Deep learning models have been utilized in achieving full automation of tasks that were previously conducted manually such as construction cost estimation. Deep learning models can be used to analyze deep structures in different domains such as natural language, speech recognition, image recognition/processing, and video/voice recognition [19].

There are several architectures that can be implemented for deep learning models. These architectures include convolutional neural networks, recurrent neural networks, convolutional encoder-decoder networks, fully convolutional networks, restricted boltzmann machines (RBM) [1, 4, 5, 6, 8, 9, 11, 12, 14, 15, 20, 21, 30]. Each of these architectures has its uses and application compatibilities.

2.2 Web-based price database

Wu *et al*. [33] defined web-based price databases as a collection of construction price data, stored, accessed, managed, and updated electronically from a computer or computing device. The existing industry-wide web-based prices databases are tabulated in Table 1.

Table 1. Existing web-based price database

Database	**Location**	**URL**
RS Means	USA	www.rsmeans.com
BCIS Online	UK	www.rics.org/ssa/products/data-products/bcis-consrtrction
Presto	Spain	www.presto.com
Batiprix	France	www.batiprix.com
Free Construction Cost Data	International	www.allcostdata.info
Compass International	International	www.compassinternational.net

Source: Presto [27].

According to Presto [27], these databases contain details about and work units, however most of these databases rely on proprietary formats or require a fee to access/utilize the database.Since every database has its own unique coding system for work units and resources, the seamless transfer of data across various platforms is a major challenge to various users of these databases. . Furthermore, since these coding systems do not act as a WBS (Work Breakdown Structure), estimates are created by simply picking predefined concepts from databases, creating only the very specific items needed in a particular project, which is carried out manually [27].

3. PROPOSED METHOD

The proposed method utilized the design science research (DSR) approach in developing the framework for integrated web-based price analysis system [23,31]. The proposed method consists of three steps in generating the cost estimates (Fig. 1): (1) Step (1) – information requirement identification – define the funtional requirement which are the input parameters. For example, materials, quantities, classifaction format, unit costs, markup, locations. The input parameters is stored in an object. Step (2) – convolutional neural networks (CNNs) information mapping development – the functional requirement which is stored in an object will be retrieved, CNNs will be constructed and mapped to each input parameter to sense for change and update automatically. Step (3) - cost estimate computation – the updated object in Step (2) containing quantities and unit costs will used to compute cost estimates . Step (4) evaluation – evaluating the proposed method by comparing a cost estimate based on the developed CNNs information mapping with manually created estimate using existing BIM software. The proposed method is expected to reduce the manual efforts needed to match materials from building design with the appropriate cost components and improve accuracy of cost estimates. Therefore, this method helps address the human input issues pointed out by [2, 3, 23,34].

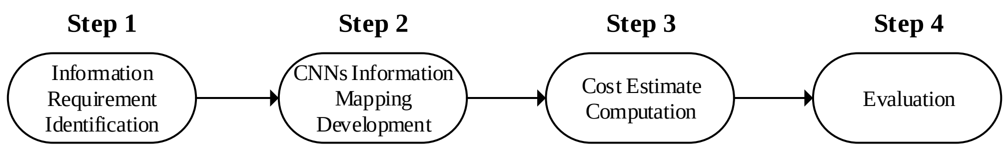

Fig. 1. Proposed CNNs information mapping development method.

4. EXPERIMENTAL RESULTS AND ANALYSIS

The proposed method was tested in an experiment of estimating the cost of the columns, walls, formworks, slabs components. The implementation details are described as follows:

Step 1 – Information Requirement Identification

Defined functional requirement (structure) for all input labels, including information about each variabes (id, unit, materials, description, date, quanities, equipment, unit cost, markup, location), all annotations (id, corresponding variables) as well as the defined categories (in this case for example walls or columns, all represented by individual IDs). The construction projects on which the proposed methods have been applied involve mainly the production of concrete elements. The following construction elements and temporary elements were modeled in the corresponding BIM: columns, walls, formworks, slabs. The input label parameters is stored in an object.

Step 2 – Convolutional Neural Networks (CNNs) Information Mapping Development

Many currently used CNNs rely on the COCO Data-set [18]. Facebook's Mask R-CNN [13] has provided promising results for machine learning in previous applications. The network itself also relies on the COCO data format as a basis. Thus, the authors chose this schema as a basis for the generation of the input labels. The functional requirement which was stored in an object, was retrieved, CNNs was constructed and mapped to each input label parameter to sense for change and update automatically.

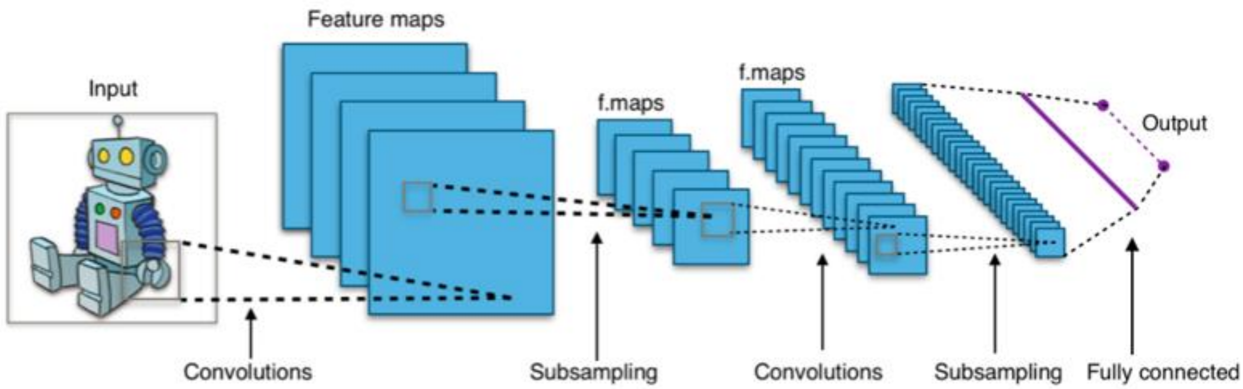

Fig. 2. CNNs architecture adopted. Source: [19]

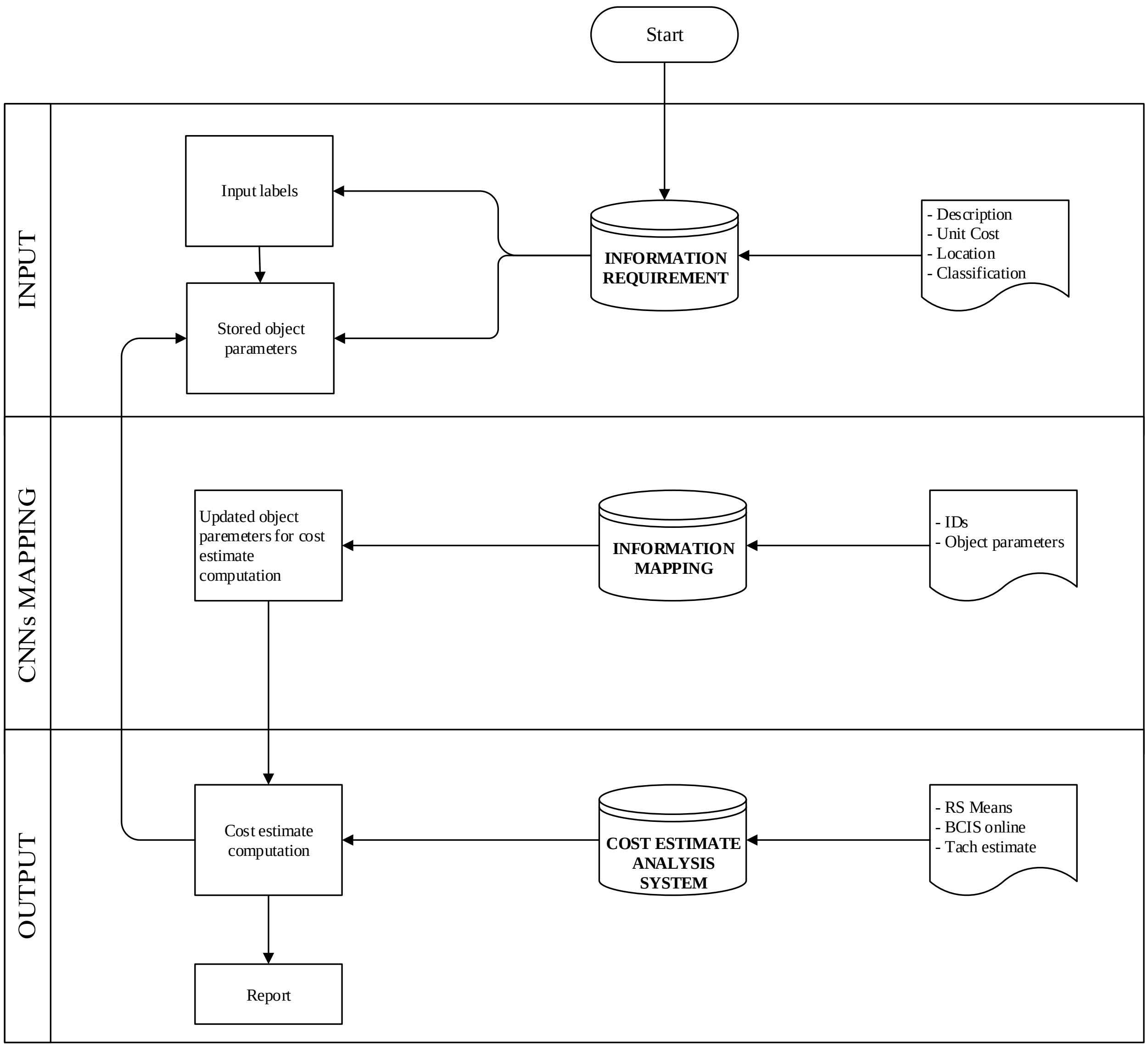

Fig. 3. Deep learning mapping flow chart for cost estimates computation

Step 3 – Cost Estimate Computation

The updated object in Step (2) containing quantities and unit costs was used to compute cost estimates

Case study

The proposed methods were tested on observation data from multiple construction sites, resulting in 42,787 labeled construction elements on 1300 images. The machine used for this test is a Windows 10 system equipped with an Intel Xeon E5-1630 CPU @ 3.70GHz, 16 GB DDR4-RAM, AMD Fire Pro W4100 8GB RAM, and a 10GBit network connection. The entire automated updating of price variables process took around 5 min, outperforming manual updating of price variables significantly. During this time, all Variables (close to 20 GB) were downloaded from a NAS (Network attached storage) and randomly added to the training, validation, and test data sets. Additionally, the corresponding label files in JSON format were generated.

The method was validated through human evaluation on all labels for the tested construction sites. The label projection worked without failure for all built construction elements in terms of generating a valid convex hull as the existing elements have been verified against amanually created ground truth. Since no issues were found in a set of over 42,000 snippets, the projection can be regarded as working correctly.

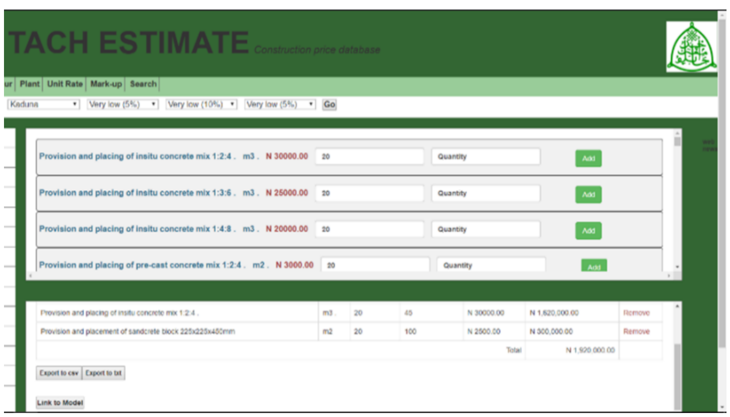

Fig. 4. The web-based cost estimates analysis system showing cost estimation.

Step 4 – Evaluation

The automatically generated cost estimate have a slight deviation from the actual construction cost. This deviation could be as a result of the following reasons: Errors in cost estimation araising from undocumented variations, large scale deviations when using real-world coordinates, construction inaccuracies and modeling inaccuracies.Since all elements were validated in the cost estimate vs. actual construction cost, construction inaccuracies can be disregarded in this research. Otherwise, the element would not have been classified as “actual construction cost” and would not have been labeled at all. Thus, the deviations, in this case, are minor and arise from an aggregation of the mentioned reasons. The overall accuracy of the automated system was calculated to be 98.16%.

5. CONCLUSION

Existing cost databases do not update automatically, with ever changing market reality/prices which led this research to integrate deep learning technique in the development of a web-based price analysis system to address the shortcomings of existing databases. The proposed automated system was tested and implemented in a case study in Detroit, MI, and Lagos, Nigeria. The case study established that the automated system has a 98.16% accuracy and it is adequate for cost estimation. The study recommends that emphasis should be made on deep learning techniques that can be used, to modify existing information systems to provide additional functions that best suit construction organisation needs. This study contributes to the existing body of knowledge in area cost estimation by proposing an alternative system that increases accuracy and reduce human involvement, so cost estimators can focus on other pressing matters.

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