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A FRAMEWORK TO INTEGRATE BIM WITH ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING-BASED PROPERTY VALUATION METHODS

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ABSTRACT:

Property valuation is of extreme importance since variations in the real estate market enormously influence people's life. The main goal of Automated Valuation Models (AVMs) is to calculate the market value of a large number of properties with an acceptable accuracy. The Hedonic Price Model (HPM) is the most widely used AVM for the valuation purposes. Despite its simplicity, ease of use and straightforwardness, HPM lacks the capability to address the non-linear relationships between different value-related factors. Hence, researchers have developed other state-of-the-art property valuation methods based on the advancements in computer science including Artificial Intelligence (AI), Machine Learning (ML), computer vision and deep learning. Design, development, and validation of such advanced AVMs require establishment of a database including data on the different influential factors. Two types of factors are used in the literature, including textual and visual features. Reliable data sources are required for the implementation of AVMs since the accuracy of the provided valuations is definitely linked to the reliability of the used real estate databases. Building Information Modelling (BIM) provides precise information on different components of properties. Although some scholars have tried to use BIM for property valuation, BIM benefits in different valuation procedures have not been fully investigated. Hence, this paper provides a framework that consider BIM capabilities to be integrated with different stages and processes in property valuation, especially in relation to advanced AVMs based on AI and ML.

1. INTRODUCTION

Variations in the real estate market enormously influence people's life, so house price measurement is of extreme importance (Xu and Zhang, 2021). Traditional valuation practices are based on the direct inspection from which the valuation professionals estimate the value of the subject properties (Chan and Abidoye, 2019). However, due to several reasons such as subjective nature of the valuers' judgments (Achu, 2013), client influence (Achu, 2013) and difference in the skills and experience of the valuers (Paris, 2008), scholars believe that the traditional valuation practices are not capable of presenting precise and reliable property prices (Abidoye and Chan, 2017).

In order to address the drawbacks associated with individual valuations, researchers have extensively investigated the development of Automated Valuation Models (AVMs). AVMs are decision support tools that process real estate information through computer applications in arriving at a property valuation figure (Chan and Abidoye, 2019; Renigier-Bilozor et al., 2019). Although adoption of AVMs requires establishment of a data set including a large amount of data regarding different features of the properties and historical real estate transactions (Pacharavanich et al., 2000), they can provide accurate and reliable estimations, in a fast, efficient and cost-effective way (Ciuna et al., 2017).

Valuation methods have been evolved since the first efforts for real estate appraisal. The Hedonic Price Model (HPM) is the most widely used AVM for the valuation purposes. Researchers have also developed more advanced property valuation methods based on the advancements in the computer science including Artificial Intelligence (AI), Machine Learning (ML), computer vision and deep learning. Design, development, and validation of such advanced AVMs require establishment of a database including data on the different influential factors. Two types of factors are used in the literature, including textual and visual features. Reliable data sources are required for the implementation of AVMs since the accuracy of the provided valuations is definitely linked to the reliability of the used real estate databases.

Property valuation should incorporate the benefits of three-dimensional (3D) models since the nature of the real estate is 3D. Indeed, 3D features significantly affect the value of the properties from both structural and visual aspects. Hence, 3D modelling and 3D GIS should be used for the collection of data and information on different value-related 3D features to establish the required data base for advanced AVMs (El Yamani et al., 2019). The literature indicates a growing trend in utilizing 3D models for valuation purposes since they are a rich source of useful semantic and geometric information on different parameters related to the properties (Mete et al., 2022).

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Among different 3D models, Building Information Modelling (BIM) provides precise information on different components of buildings. Hence, it could be considered as a rich source of information for valuation purposes (El Yamani et al., 2021). Some scholars have tried to introduce or use BIM for property valuation practices (Arcuri et al., 2020; Celik Simsek and Uzun, 2021; El Yamani et al., 2019; Su et al., 2021). However, BIM benefits for different stages of valuation process and its integration to advanced valuation procedures have not been fully investigated. Hence, this paper provides a framework that consider BIM capabilities to be integrated with different stages in advanced AVMs based on AI and ML. Accordingly, section 2 discusses different property valuation methods, focusing on AI and ML-based methods. Section 3 describes different valuation factors. Then, section 4 introduces BIM capabilities for the property valuation field. Subsequently, section 5 establishes a framework to integrate BIM with advanced valuation methods. Finally, section 6 concludes the paper and presents avenues for further research.

2. PROPERTY VALUATION METHODS

The literature introduces three basic approaches for property valuation, including:

- Comparative or market approach, which consists the prediction of the value of a subject property in comparison to similar properties transacted in the same market using historical real estate data sets (Pagourtzi et al., 2003).
- Income or yield approach, which is based on the capitalized value of the income flow that a piece of income-producing real estate asset can provide. (Glumac and Des Rosiers, 2021).
- Cost approach, which calculates the market value of a property using the land value plus the replacement cost deducted by an appropriate depreciation (Arcuri et al., 2020).

In addition to these three basic approaches for property valuation, literature review led to identification of various AVMs developed using big data analysis. Hedonic Price Model (HPM) is the most widely used AVM (Wei et al., 2022). HPM is a valuation method which is established based on the development of an Ordinary Least Square (OLS) regression or a Multiple Regression Analysis (MRA) using different property features as independent variables to predict the value of the real estate asset as a dependent variable (Abidoye and Chan, 2018a; Shen et al., 2022). Typically, single-stage regression equations are used in HPM to simply estimate the value of properties based on different physical and non-physical factors (Sirmans et al., 2005). In spite of its simplicity, ease of use and straightforwardness, HPM lacks the capability to address the non-linear relationships between different value-related factors (Abidoye and Chan, 2018b).

Geographic Information System (GIS) and spatial analysis have been among the first techniques which were used to improve the property valuation procedures, especially through incorporation of various geographical and locational features (Pettit et al., 2020; Wyatt, 1997). Fuzzy logic is another type of advancement in data processing techniques that has been used for valuation purposes (Bagnoli and Smith, 1998). Forecasting algorithms based on time-series analysis, especially the Auto-Regressive Integrated Moving Average (ARIMA), as well as Multi-Criteria Decision Making (MCDM) methods and optimization methods like Genetic Algorithm (GA) have also been applied for real estate valuation (Chmielewska et al., 2020; Maliene, 2011; Tse, 1997).

2.1 Artificial Neural Network

In addressing the aforementioned shortcomings of the HPM, another field of research was pursued to apply technological advancements in computer science and AI in the property valuation sector. Artificial Neural Network (ANN) is one of the major techniques that has been employed for valuation purposes (Abidoye and Chan, 2017). The ANN computational model could deal with non-linear relationships, thereby support a broader range of variation than HPM. ANN can forecast housing prices after learning the underlying relationships between the input variables related to the real estate and their corresponding outputs through a complex network of artificial neurons (Sirmans et al., 2005).

Various studies have been undertaken to compare the performances of HPM with ANN in property valuation. Overall, it has been asserted that ANN shows a mean absolute error rate of between 5 and 10% for property valuation procedures, while HPM presents a higher average between 10 and 15% (Abidoye and Chan, 2017; Mora-Esperanza, 2004).

2.2 Machine Learning (ML)-based models

In addition to ANN, capabilities of Machine Learning (ML) methods have also been widely scrutinized in the literature for real estate appraisal. ML is a cutting-edge AI-based technique that is used to provide accurate predictions through consequential learning of the input data. Application of ML techniques in property valuation field is increasing in the literature. Different studies emphasize that the accuracy of ML-based AVMs is higher than the AVMs developed based on HPM (Hammad, 2018; Ho et al., 2021). The most widely used ML methods for property price forecasting are:

- Decision tree: decision tree is a non-parametric algorithm that could be used both for classification and regression. The goal is to develop a model that estimates the value of a target variable through supervised learning of simple decision rules inferred from the input data features. Despite its simplicity to be developed and be interpreted, decision tree method can lead to overfitting, and small variations in data can cause a dramatic change in the results (Sing et al., 2020).
- Random Forest (RF): In order to solve the limitations of the decision tree algorithm, ensemble techniques such as bagging and boosting are used. Ensemble learning methods apply multiple learning models to produce one optimal predictive model. RF algorithm works based on the bagging principle, which is also known as bootstrap aggregation. Bagging is based on the iteration of selecting a random sample from the data set with replacement of the training set and fitting trees to these samples known as bootstrap. Accordingly, each model is independently trained, and the final result is generated through combining the results of all trees and identifying majority voting. This process is known as aggregation (Ho et al., 2021; Masías et al., 2016; Teang and Lu, 2021).
- Boosting and Gradient Boosting (GB): As previously mentioned, boosting is a manner to overcome the drawbacks of decision tree model. Boosting, like bagging, is an ensemble learning method that has been

developed based on the idea of combining a set of weak learners, typically decision trees, to increase the strength of the model. The difference between boosting and bagging is that the boosting produces models in a sequence, and the final model reaches the highest accuracy, while the models in the bagging are created in parallel. GB is an algorithm that has been established based on traditional boosting methods, but it has the ability to reduce the residual of the previous trained model and build a new model in the gradient direction of the residual reduction (Almaslukh, 2020; Ho et al., 2021; Zulkifley et al., 2020).

- Support Vector Machine (SVM): SVM is a supervised learning model that is mostly used for classification. The main idea in SVM is finding hyperplanes in an N-dimensional space (N is the number of features) that can divide objects to different classes while maximizing the distance between data points of each class to the separating hyperplanes. For better classification, it is possible to project the inputs into a higher dimensional feature space in order to find a kernel function for any dataset to be linearly separated. SVM can also be employed as a regression method that is called Support Vector Regression (SVR). The main idea of SVR is same with the SVM so that the input data can be mapped into an m-dimensional feature space employing nonlinear mapping in order to build a linear model in the feature space (Chen et al., 2017; Ho et al., 2021; Wang et al., 2014; Zhang, 2012).
- K-Nearest Neighbor (KNN): KNN is a non-parametric supervised learning method that could be used for both classification and regression processes. For the regression, the output is the value of each object based on the k most similar objects in the training set. This value is computed based the average of the values of k nearest neighbors. The key step in the KNN algorithm is the definition of similarity between objects using Euclidean distance (García-Magariño et al., 2020; Oladunni and Sharma, 2016; Pow et al.).
- Combined or optimized methods: As previously discussed, ensemble techniques are models that are developed by combining the predictions from multiple models to find an optimal predictive model. RF and GB that are respectively established based on bagging and boosting ensemble techniques of weak learning models were introduced. There are also other ensemble learning methods that are developed based on the combination of predictions from multiple learning algorithms, such as stacking and voting. In these combined methods, two or more different learning algorithms are ensembled for improvement of the regression predictions (Shahhosseini et al., 2019; Yacim and Boshoff, 2020). Optimized methods are similar and seek to improve the accuracy of the ML algorithms using optimization techniques such as GA (Su et al., 2021; Sun, 2019). Both of combined and optimized methods have been applied for improving the accuracy of the ML-based AVMs.

3. PROPERTY VALUATION FACTORS

Design, development, and validation of different AVMs require establishment of a database including data on the different influential factors (also called features or variables). Valuation methods like HPM and ML-based methods assumes that the value of a real estate asset is influenced by a bundle of features, and each of them can have a different impact on the value of the properties (Metzner and Kindt, 2017). Most of these methods attempt to estimate the value of properties as a dependent variable using development of parametric or non-parametric regression models based on different value-related factors as independent variables (Lin and Mohan, 2011).

Valuation factors could be considered as quantitative features like area, number of bedrooms, number of bathrooms and number of parking and qualitative variables like design quality, landscape view, noise level, Heating, Ventilation, and Air Conditioning (HVAC) and energy efficiency (Metzner and Kindt, 2017; Rubio et al., 2008). In terms of domain of the factors, they can be divided to:

- Micro-economic factors that are individual parameters for each property such as age, floor, area, and location.
- Macro-economic attributes that are the variations in the real estate valuation at an aggregate level, such as economic outlook and interest rates (Binoy et al., 2022; Metzner and Kindt, 2017).

Literature review led to identification of two types of valuation factors, which will be elaborated in the next two sub-sections.

3.1 Textual features

Scholars have used various textual valuation factors for the development and implementation of appraisal methods. The most widely used value-related variables in the literature were identified and presented in Figure 1. The valuation factors have been grouped under 7 categories in this study, including:

- Structural
- Internal
- External
- Living quality
- Environmental
- Geographical
- Socio-economic and legal

Some of the identified factors such as landscape view, air quality, noise level, sunlight exposure, etc. are 3D in nature, and 3D models are required for derivation of them.

3.2 Visual features

Over the last years, a new domain has been added to the research on property valuation, which is extraction of useful visual features from image data using AI and computer vision to improve the predictive performance of real estate appraisal methods (Nouriani and Lemke, 2022). Visual features have been introduced as key factors in estimating the market value of the real estate assets (Elnagar and Thomas, 2020). Accordingly, visual features extracted from images using AI and computer vision have been used separately or in combination with other textual features for real estate appraisal purposes. Many authors have used them as additional factors to textual features for the development of different types of AVMs based on HPM, ANN, and different ML-based techniques. Some of them have also evaluated the efficacy of adding such visual features to other textual value- related factors and indicated the capabilities of visual features in increasing the accuracy of the AVMs

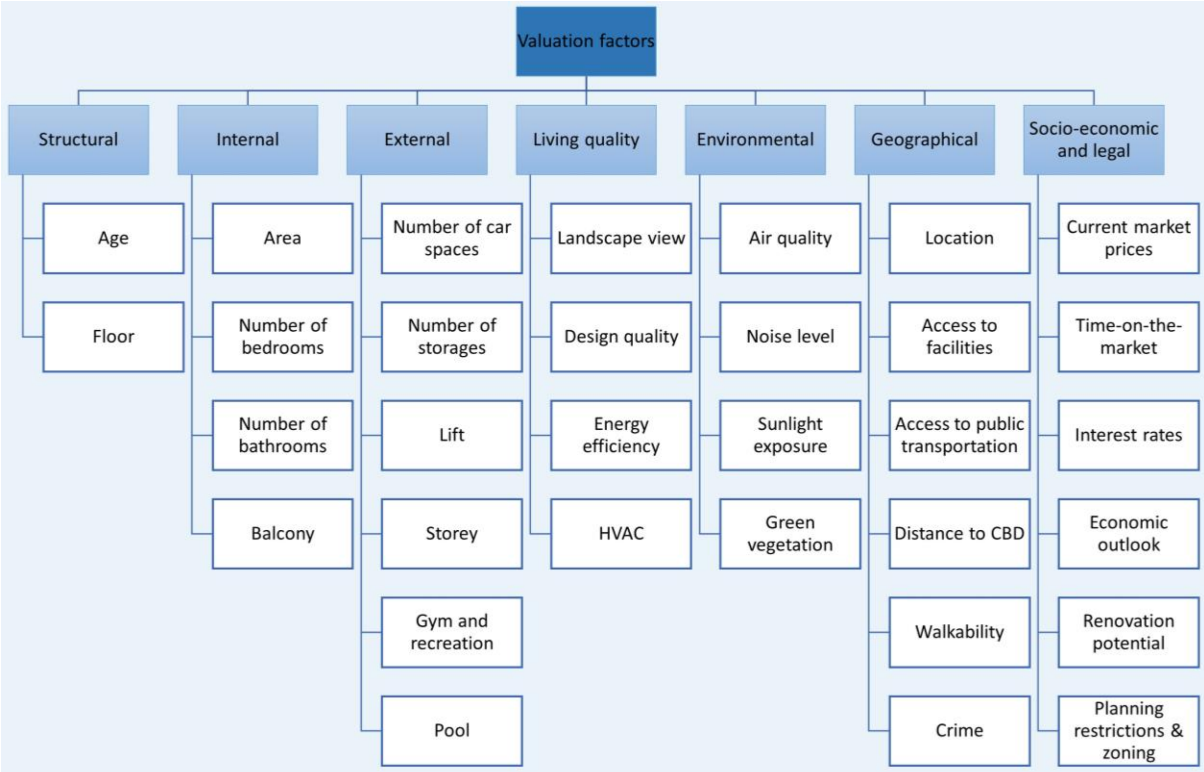

Figure 1. Textual valuation factors used in the literature for the development of advanced AVMs.

(De Nadai and Lepri, 2018; Helbich et al., 2013; Kostic and Jevremovic, 2020; Law et al., 2019; Lee and Park, 2020; Liu et al., 2018; Muhr et al., 2017; Nouriani and Lemke, 2022; Poursaeed et al., 2018; Solovev and Pröllochs, 2021).

Three types of images have been used in the literature for visual feature extraction, including:

- Interior images
- Exterior images
- Remote sensing images

For the aim of extraction of internal, external and neighborhood and locational visual variables, computer vision methods such as Speeded Up Robust Features (SURF) (Ahmed and Moustafa, 2016) and deep learning methods such as Convolutional Neural Network (CNN) (Bin et al., 2020) have been employed. CNN, as a class of ANN techniques in AI, has been widely utilized in the literature to analyze visual imagery (Lee and Park, 2020). CNN is primarily employed in order to address fundamental issues in computer vision such as classification, segmentation, object detection and localization (Perez et al., 2019). Through deep, robust and accurate interpretation of real estate images, CNN has been used for capturing useful visual features for property valuation practices (Zhao et al., 2019).

4. BIM AND PROPERTY VALUATION

Property valuation should be undertaken considering the 3D nature of the houses since the real world is 3D in nature. To be more specific, the concept of value originates from intrinsic features associated to the properties as 3D objects and external factors related to the 3D environment (El Yamani et al., 2019). With 3D data modelling and visualization, buildings and houses could be represented in a 3D context. Accordingly, 3D GIS and 3D modelling can significantly facilitate different domains of real estate business, such as property valuation (Yu et al., 2014). Todays, 3D data sources such as BIM, 3D city models (CityGML) and 3D cadastre have provided a great opportunity for researchers to derive valuable information regarding different internal and external components of the buildings and properties. Such reach sources of information could be utilized for property valuation purposes as well (El Yamani et al., 2021; Tomić et al., 2012; Yu et al., 2014).

Among different 3D models, BIM can constitute internal and to some extent external parameters specific to different buildings, so it could be used as an effective source of physical, geometric and semantic data for different procedures in property valuation process (Arcuri et al., 2020; El Yamani et al., 2021; Mete et al., 2022). In addition, it has been proved that AI and ML methods can be developed using BIM-related data and techniques (Zabin et al., 2022).

As already mentioned, basic approaches for property valuation and AVMs established based on HPM, AI and ML consist of different steps. Some studies have attempted to introduce BIM capabilities for property valuation (El Yamani et al., 2019) or develop a valuation methodology using BIM (Celik Simsek and Uzun, 2021). Each of the relevant studies in the literature has investigated the benefits of BIM for one or some parts of property valuation procedures, e.g., development of ML-based valuation models using textual data extractable from BIM (Su et al., 2021), adoption of cost approach using BIM (Arcuri et al., 2020) and introduction of some 3D factors for property valuation that could be derived from BIM and 3D GIS (El Yamani et al., 2021). However, there is no study that completely review all the different components of the property valuation methods, including basic approaches, simple and advanced AVMs and different textual and visual value-related features, and provide BIM possibilities to be integrated with these components at different stages.

5. FRAMEWORK

As previously mentioned, property valuation is a complex process that incorporates different stages and components. For the establishment of the valuation process, it is important to identify the valuation method and valuation factors. The valuation method could be developed based on basic approaches of market, yield or income, as well as AVMs based on HPM, AI and ML. The valuation factors can also be divided into two categories of textual and visual.

BIM as a rich source of 3D data can be used in different stages of valuation process. First, it could be used to prepare the data base that is required for the development of different AVMs. This could not only cover textual features but also include visual features. Some 2D textual features could be directly extracted from BIM. Some 3D factors can also be derived from computations and analyses through BIM and 3D GIS. In addition, BIM representations could be analyzed for the extraction of visual features using AI and computer vision. BIM representations are 3D models which provide detailed visualizations of the various dimensions of the properties indicating their different visual characteristics such as level of decoration and luxury. 2D photos used in the literature for extraction of visual features may be taken from different angles, have different resolutions, and more importantly not provide a complete and accurate overview of the houses. Such limitations can decrease the reliability on the visual features extracted from 2D images, whereas BIM 3D representations can be considered to address this issue.

Second, computational procedures in BIM in relation to Quantity Take-Off (QTO) and Bill of Quantities (BoQ), as well as Life Cycle Analysis (LCA) and Life Cycle Cost (LCC) estimation could be employed for calculation of the components of the cost approach-based property valuation, including reconstruction cost and depreciation cost (Arcuri et al., 2020; Khodabakhshian and Toosi, 2021). To be more specific, BIM provides efficient tools for automatic construction cost estimation through QTO, as a list of individual construction units. These items can be then multiplied by their unit cost in order to calculate the cost of each activity of the construction project through BoQ (Fazeli et al., 2021). LCC also consists of all costs and revenues associated with the acquisition and ownership of a real estate asset from the initial steps of the construction to demolition and disposal. Accordingly, LCC is completely interlinked with the depreciation cost, which comprises all the costs reflecting the loss of value of a building asset. Depreciation could be caused by different factors, including physical deterioration, functional obsolescence and economic obsolescence (Liapis and Kantianis, 2015; Mansfield and Pinder, 2008).

According to these different possibilities that BIM can provide for development of advanced AVMs, a framework that comprehensively illustrates different property valuation processes from properties to estimated values while identifying BIM capabilities to be integrated into the relevant stages is presented in Figure 2. The processes presented in Blue show all possible steps of the property valuation from properties to the estimated values while focusing on the applications of AI, ML, computer vision and deep learning in the different stages. In addition, the possible integration of BIM with the different stages of the valuation processes has been depicted using Gray color.

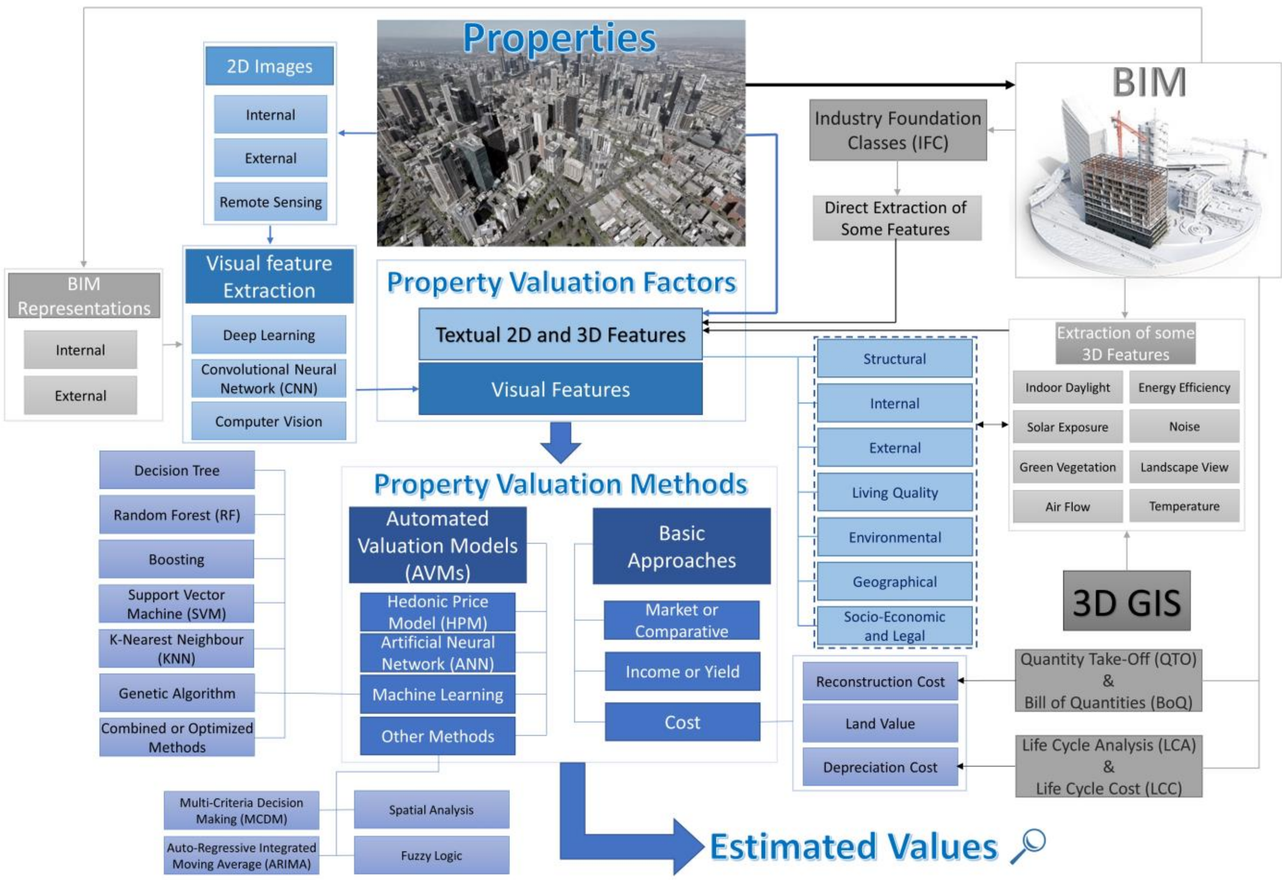

Figure 2. A comprehensive framework to integrate BIM to AI and machine learning-based property valuation methods.

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This framework demonstrates how BIM can be utilized to access required data and information for the development of advanced AVMs, especially using AI and ML. This could be provision of some 2D and 3D textual features and some visual features. However, it should be highlighted that BIM can provide partial information required for valuation purposes. Data on some factors such as socio-economic and legal factors should still be collected from other resources than BIM. In addition, many of the mentioned 3D factors should be extracted through combination of BIM with other 3D models, such as CityGML.

6. CONCLUSIONS

Property valuation can substantially benefit from 3D technical achievements in BIM technologies. BIM provides the geometry, topology and semantic characteristics of building elements. Such detailed data and information could be employed for the preparation of the required data bases that are necessary for AI and ML-based property valuation methods.

This paper comprehensively investigates the whole processes related to property valuation from properties to estimated values, concentrating on the applications of ML, computer vision and deep learning in different pertinent stages, as well as the benefits of BIM to be integrated with different procedures in advanced valuation methodologies.

However, this paper only presents the BIM capabilities for property valuation processes. Future work can seek to identify the benefits of other sources of 3D data for property valuation such as digital twin, 3D cadastre and city GML to extend the presented framework in this paper. Such an extended framework could be a baseline for future real estate appraisal practices that try to benefit from rich sources of 3D data and information.

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