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Automated Visualization Of 2d Cad Drawings To Bim 3d Model Using Machine Learning With Building Predictive Maintenance Modelling System

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Abstract

In recent years, the ease of adaptation of BIM technology was difficult although it brought significant importance and contribution in AEC industry. Different areas use BIM technology however workload necessary to integrate such technology are time-consuming and not easy to learn as BIM practices needs user to bear a lot of field experience. Some of the major challenges to this technology adaptation relates to the classification and analysis aspects of 2D CAD drawings to be converted into a 3D BIM model. Having said that, the article proposed a direct and automated solution with the utilization of machine learning concept to ease the labor-intensive conversion process. With machine learning model's intelligence to correctly identify different entities in a 2D drawing, the classified information can be built to the visualization process of 3D BIM model. As additional uniqueness to the project, a predictive maintenance analysis with a different machine learning model was explored. The evaluation of the project was based on the accuracy of the neural network in indicating the building elements for visualization on the Autodesk Revit.

Keywords—2D CAD Drawing, 3D BIM Model, Automated Visualization, Machine Learning

Introduction

A digital representation of physical and functional attributes of a building with the collection of these information acting as first step to provide decisions throughout the phases from design to demolition is known as Building Information Modeling (BIM). (Zhang, 2009) It is known that BIM provides such integrated information for the benefit of facility maintenance and operation (Law et al, 2021), however construction process referencing on 2D drawings contributes to greater than 90% of current buildings in U.S. (Cho & Liu, 2017) BIM is also described as the object created in a multi-dimensional virtual space in the format of 3D model including data management in the project like structures, electrical routing, plumbing structure, dimensions, objects and others. Besides that, the major next step to the technological advancement of AEC industry which the government support is the inclusion of BIM. Over the years, the market area for BIM technology is growing in interest with the ongoing development of multiple software designed for BIM purposes such as Autodesk Revit, Revizto, Autodesk Navisworks, ArchiCAD, Vectorworks Architect and others. (Byun, 2020)

Consequently, the current solution ideas on this conversion process from 2D to 3D is slowly gaining recognition from the positive research results so it decreases duplication workload and lowers the limitations for technical and economical gaps for smaller scale companies in the adoption of this technology (Choi et al., 2018) In Singapore, governmental requirements states the need for BIM model documents on architectural and engineering aspects for projects above 5000m^2 by Building and Construction Authority (BCA). Before the existence of BIM technology, there were no documents of such manner as shown by Housing Development Board (HDB), more than 1 million apartments do not have this BIM documentations. (Lim et al., 2018) Part of the adoption of BIM technology would reduce amount of change orders and requests for information from 37%-48% and 43%-68% respectively based on provided case studies.

Design cost would rise by 31% which shows that adoption of BIM as of currently does not provide a cheaper and efficient methodology since it is a complex and advance type of research field. With that, the question of solving this issue was circulated towards the theory on automated generation process on this 2D data to the 3D object from the utilization of image data, laser scanning data, drawing data or predictive data algorithms. (Yang et al., 2020) The major usage of 3D models is often observed in robotics, cultural heritage buildings, entertainment industry, city modelling and others. Conservators would simulate culture heritage monuments in a 3D format to ensure that proper restoration process can be carried out in the future. Entertainment industry has shown clear indications of time-consuming labour needed to generate such models despite the end results may often lead to lack of details although artists spend hours on it. (Pitzer, 2014)

Over the years, this visualization process suggested from either documented data or undocumented data bears the largest obstacle to the growth of this BIM technology. Even with the growing demand in different countries because of this technology's benefits, it is only progressing slowly and having constant practice over the years. As simple as it may sound, the conversion of building data from CAD data exploitation while creating a BIM system from it shows a high level of difficulty. (Barki, 2015) Stakeholders for companies would be given a clearer understanding of the design and management process so they can provide more significant feedback with a 3D model with large amount of information loaded. The usage of 3D modelling has a high level of awareness in terms of working principle for many projects (Yetis, 2019) Some of the research questions that would be discussed upon for this article's issues are listed below:

- ✓ Can the expectations of the automated process and inclusion of sufficient results support this idea with a machine learning model?
- ✓ Would the process duration be decreased significantly as compared to the time consuming labour method?
- ✓ How accurate and precise would the requirement of the 3D model so that it can be put into industrial practice?

Aim and Objectives

The aim of this project is to design and develop an automated process algorithm to visualize a 2D CAD drawing to a 3D Building Information Modelling (BIM) model along with a building maintenance predictive model for inspection and monitoring purpose. The following are the objectives from this research:

- To develop an appropriate machine learning algorithm to automatically extract relevant information from a 2D architectural drawing for feature classification
- To design a program for automated visualization of BIM 3D model as a standalone application
- To formulate a simple machine learning algorithm for predictive maintenance application using BIM data
- To appraise the efficiency and performance of the machine learning models developed

Proposed Methodology

In this paper, the concept is to utilized machine learning to provide to overall 3D BIM Model visualization process in an automated manner while providing design predictive maintenance analysis as an additional feature added to the project. There will be two machine learning model involved in this research. Based on the 2D drawings provided in this research, it will be pre-processed to derive some of the main elements of the building which are the fundamental portions of any construction buildings. By detecting the wall, window and door components, this information is fed to the model which runs through a series of testing and evaluation to provide optimum classification results. The same logic is applied to the second model as well for predictive maintenance analysis where in this scenario utilizes the building data such as temperature.

The overall system will be conducted with the creation of a graphical user interface that would read onto the required CAD drawings and BIM data while launching the AutoDesk Revit software upon completion of the visualization process. The developed user interface will be conducted using Qt Designer which is utilized under Python programming language to compile all machine learning and other codes required for this system.

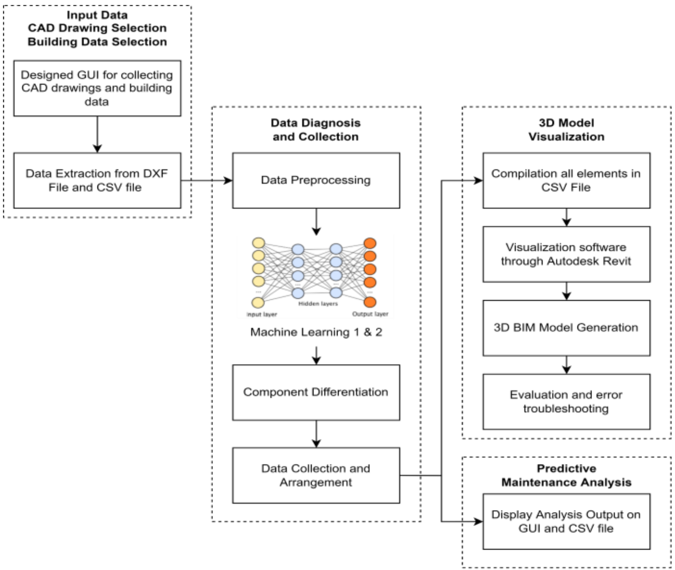


Fig. 1 *Overall System Block Diagram*

One of the very first implementation logic for this system relates to the data extraction from the CAD drawings for the computer to compute which are wall, window or door entities. After determining all these elements, the information is processed in a series of array manipulation to rearrange the data in a specified manner for machine learning model to learn. The concept of placing vertical and horizontal line determination with the wall thickness factors allows the determination of the wall element using ezdxf library. However, during the development stage, it was found that the given CAD drawings provided by Jurusy Perunding Sdn Bhd consist of diagonal oriented walls which was unable to be determined. Hence, the implementation of the diagonal wall detection was implemented in the code structure as well shown on Fig. 2.

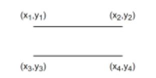
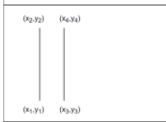
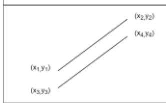
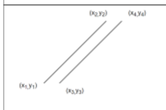
Line Drawing	Line Type	Conditional Requirements
	Horizontal	$y_1 = y_2$ $y_3 = y_4$ $\|y_3 - y_1\| = thickness\ of\ wall$ $\|y_4 - y_2\| = thickness\ of\ wall$
	Vertical	$x_1 = x_2$ $x_3 = x_4$ $\|x_3 - x_1\| = thickness\ of\ wall$ $\|x_4 - x_2\| = thickness\ of\ wall$
	Diagonal A	$x_1 = x_3$ $y_1 \neq y_2$ $y_2 - y_1 = y_4 - y_3$ $\|y_1 - y_3\| = thickness\ of\ wall$
	Diagonal B	$y_2 = y_4$ $x_2 \neq x_1$ $x_2 - x_1 = x_4 - x_3$ $\|x_1 - x_3\| = thickness\ of\ wall$

Fig. 2 *Concept for Data Extraction from CAD drawing*

Machine Learning Model (Visualization)

For this model, it is developed with a fast forward neural network (FFNN) which is a simple and direct neural network utilized for classification of numerical datasets. The model is configured to categoricalcrossentropy loss function with Adam optimizer and other hyperparameters were adjusted accordingly to satisfy the overall outcome for accurate classification. The features involved in this classification are mainly on derivation of LINE and BLOCK entities that are provided a set of conditions to distinguish the building elements. The different line variation involved are vertical lines, horizontal lines, and diagonal lines in two different orientations. This numerical information is stored in the form of CSV file which is fed into the neural network model to give out the final output layer result where the provided information is wall, window, or door.

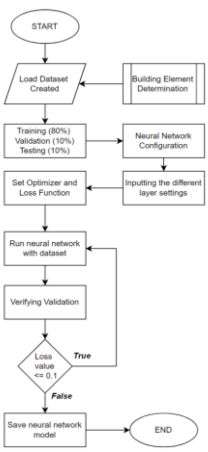


Fig. 3 *Machine Learning Model Training Flow*

Machine Learning Model (Predictive Maintenance)

After all the different types of machine learning model available, it was found that linear regression predictive algorithm is sufficient to run this process. Due to the lack of building data, a simulation of an existing building was conducted using Design Builder to collect some of the relevant information through outlining a few of the zones in the building. The main information considered from this simulation data is the steady state heat loss and comfort temperature of every room available in the building. This information is fed into the model for linear regression predictive for classification on which rooms contains high, low, or nominal heat conditions. This concept is utilized to study how building designs can be processed through this predictive maintenance analysis to indicate whether the building design can be improved before the construction stage. The usage of existing building data would be implemented to denote how the new building designs may have some issues by the trained neural network. This concept is utilized in this research to provide an additional enhancement to current BIM model adaptation to promote the possibility of having a more advanced analysis while in this paper, it utilized a simple approach to verify the workability of the system proposed.

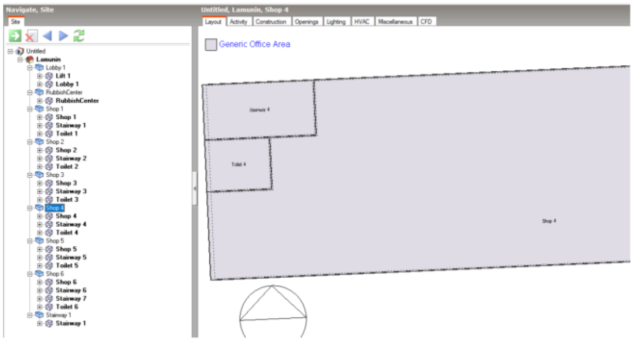


Fig. 4 *Simulation of Data from DesignBuilder*

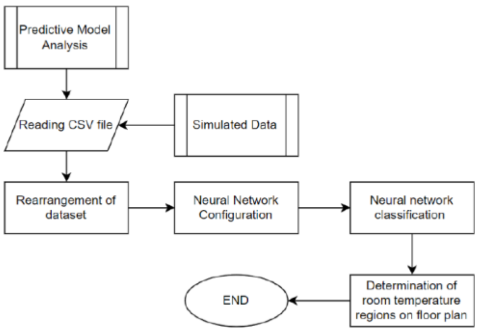


Fig. 5 *Predictive Maintenance Process Flow*

Automated Visualization System for 3D BIM Model

After the machine learning model can classify the different building elements presented by the 2D CAD drawing provided in the form of CSV file, this file is directed to the AutoDesk Revit API code which will read on the data to reproduce the building element in a three-dimensional space on the software. This step relates to the visualization process of the system developed. The coordinates of the wall elements will be analysed and alongside the height values, it will extrude the wall elements accordingly. The other two building elements known as door and window will be created based on the location of the wall element as well. Upon completion, the AutoDesk Revit API code developed will be visualizing the entire 3D BIM Model. A Pyrevit library command would be utilized to generate a specified building element in Autodesk Revit. The wall element would bear highest importance as it would be the indicating condition that a door or window element is present. The elevation floor plan provides the positioning and height of the building elements. The extraction of height information is required from the elevation floorplans while the specific coordinate location of the three main building elements is required for this visualization process.

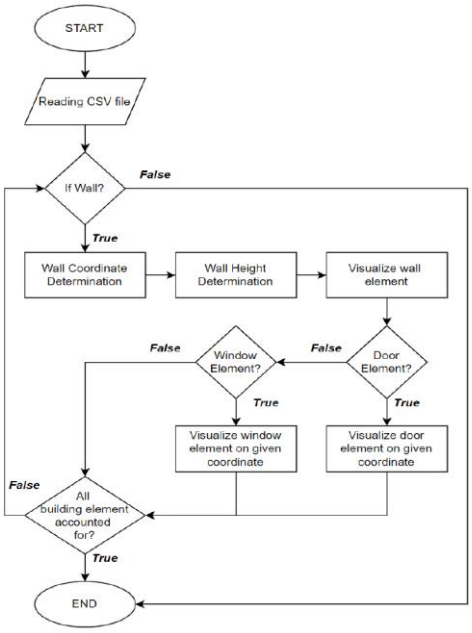


Fig. 6 *Visualization of 3D BIM Model Process Flow*

Simulation Results and Evaluation

Classification of Neural Network

Two different datasets were utilized in the evaluation of the neural network's capabilities to classify the building elements. The first set would be the default Lamunin Building dataset and the second set was created by inputting unknown variables that requires the neural network to run proper classification process. The default dataset is utilized to train the neural network while the other is for testing purposes. In Table I below, it indicates the configuration of hyperparameters of specific machine learning model. A notable understanding would be the dataset provided for training needs to be prepared accordingly in order to classify building elements with minimal errors towards unknown variables fed into it. The errors can be predicted as outputs which bears significant impact on the visualization process of building elements.

Table.1: *HyperParameter configured for machine learning model designed*

Machine Learning Model	Model
Loss Function	CategoricalCrossEntropy
Optimizer	Adam
Epoch	100
Input Layer	Relu
Hidden Layer	Linear
Output Layer	Softmax
Batch Size	64

Upon analyzing the results from the model with unknown dataset, it was observed that despite accuracy remains in a smooth incremental behavior, the output generated is not desirable. Fig. 7 and Fig. 9 portrays steady rise from initial epoch which suggests a learning process by the neural network from the first step in the accuracy graphs. Steady decrement is then observed on Fig. 8 and Fig. 10 for the loss graphs that concludes a reliable system is made possible. For the observed system output, high and desirable amount of correct predictions referenced from the target data was achieved from the accuracy and loss graphs. In the mind of a neural network, whenever it is fed with unknown variables, it would identify them as part of the results of predicted outputs which decreases the overall system's reliability. Hence, it can be concluded that a good dataset is able to improve the overall classification process to generate optimum amount of correct predictions.

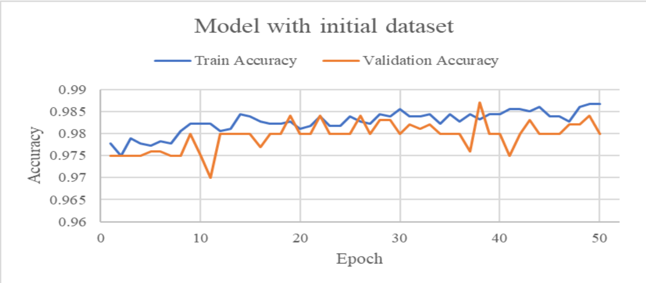


Fig. 7 *Accuracy Graphing for initial dataset*

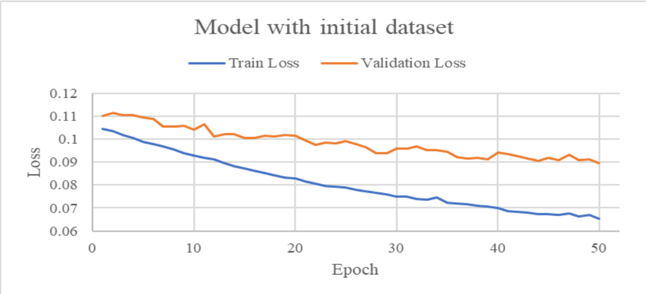


Fig. 8 *Loss Graphing for initial dataset*

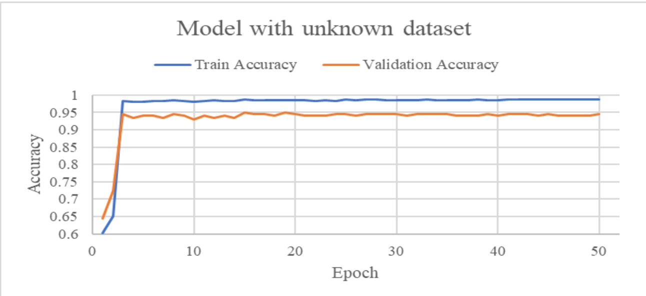


Fig. 9 *Accuracy Graphing for unknown dataset*

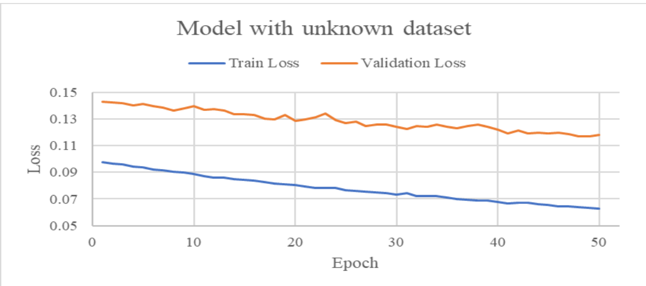


Fig. 10 *Loss Graphing for unknown dataset*

After running the visualization of 3D BIM model of the inputted building, both dataset's prediction is evaluated which found that having the unknown datasets drastically result the prediction capabilities in terms of accuracy shown by Table II. Both conditions affect the model's performance by returning different amounts of errors. Classification of the model was made possible in this system despite the errors returned as long as more good dataset can be included. This suggests this project's methodology to include a proper algorithm to build up better training process for the model.

Table.2: *Summary of Results Between Initial and Unknown Datasets*

Training Data	Initial Dataset	New Unknown Dataset
Correct Building Element Identification	95/115	83/115
Accuracy	82.6087%	72.1739%

During the literature study, majority of the research have placed an average of 80-85% range for the classification of the neural network to identify typical building elements. Hence, as a goal, the proposed methodology aimed to attain more than 85%. Through multiple testing iterations (15 testing), the model designed was able to achieve an average outcome accuracy of 85.9701% which satisfies the requirements in terms of literature study and self-proclaimed goal. Expected classification accuracy would obviously be a full 100% which means any inputs from CAD drawings should be directly visualized as the BIM model. Under real-life applications, it would be difficult to attain the theoretical and expected classification accuracy because errors would constantly appear as the neural network is also learning so it displays further rooms of improvement.

Data extraction code implemented to distinguish the necessary information to acquire a good dataset would be the main reason how the accuracy of the built neural network can perform outstandingly. Under machine learning code, there are certain configurable parameters which contributes to the performance of the model such as layers, epoch, activation functions, loss functions and optimizer. Higher complexity of floor plans were included in the project as well which bears significant impact to how the accuracy of the model is sufficient as compared to other research models.

Table.3: *Discrepancy Results by Multiple Times of Testing on Building Element Classification Accuracy*

Testing	Building Element Count	Total Element	Accuracy %
1	105	115	91.3043
2	108	115	93.913
3	97	115	84.3478
4	80	115	69.5652
5	102	115	88.6957
6	98	115	85.2174
7	106	115	92.1739
8	112	115	97.3913
9	83	115	72.1739
10	99	115	86.087
11	97	115	84.3478
12	101	115	87.8261
13	102	115	88.6957
14	95	115	82.6087
15	98	115	85.2174
	Average:		85.9710

Predictive Maintenance Model

Under this evaluation, the predictive maintenance model was given the simulated data from Design Builder software under a specified condition. The simulated data is processed by the machine learning model with the hyperparameters as shown below which operates under linear regression predictive method. The two main evaluation criteria are the coefficient of determination and loss from the machine learning model when given the dataset.

Table.4: *Hyperparameter for Machine Learning Model for Predictive Maintenance Model*

Machine Learning Model	Model
Loss Function	Mean Square Error
Optimizer	Rmsprop
Epoch	10
Layers	Linear
Addition	LSTM with 50 units

In theoretical sense, the number of variations in the predicted output with relation to input is the coefficient of determination. A linear increment pattern is shown for the coefficient of determination and an opposite effect is seen for the loss from the graphical representation shown. Overall, the dataset provided was able to return a good level of results as the coefficient of determination is high while loss is lower.

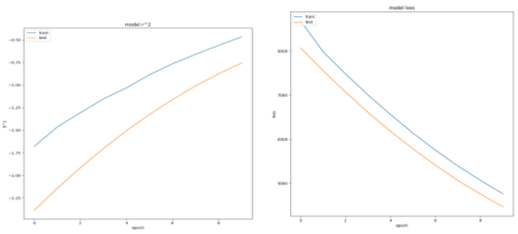


Fig. 11 *Coefficient of determination and Loss Graphical Representation for model developed*

The model was able to detect most of the room regions being at different heat regions with a good level of accuracy. Since the dataset provided was not very extension, the overall result seems minor as it is only up to 15 different rooms in a building.

TABLE.4: *Predictive Model Results*

Data Set	A
Predicted high heat regions	2 out of 2
Predicted low heat regions	8 out of 6
Predicted nominal heat regions	13 out of 15
Errors	2
Accuracy	91.3043%

A display of this result is seen on the GUI developed where it will indicate to the user the process being run and indicates the room that bears the highest heat regions. On the backend of the program, the analysis of every room is exported in the form of a CSV file.

Fig. 12 *Operability of developed GUI for overall system developed*

Under this model built, different variable in the form of conditional sets and other external factors can contribute to the overall identification of heat regions. In theory, the deduction of heat regions with reference to the data provided can be easily achieved by an experienced or specialized engineer. This concept idea is used for this system but the results are more direct than complex analysis which suggests that the reliability of this system is also based on the programmer's knowledge on how to run the deductions. Having more understanding of the possible heat regions factors can alter the model to have a more precise and accurate analysis result. By theoretical concept, it would be expected by this system to have more complex results with lengthy conditional requirements. However, due to time constraints and lack of knowledge, the direct analysis was achieved instead which is sufficient as this system aims as a possible development enhancement to the project topic.

Visualization of 3D BIM Model

The only proper results that makes the uniqueness of the project come to light is the visualization of the 3D BIM model on Autodesk Revit from the 2D CAD drawing and it would show the project's success. Different level of complexity on the floor plan drawings expresses this proposed system's efficiency. Theoretically, it would be expected to present the entire BIM model exactly from the drawings, but errors still occur. The drawings are fed individually into a self-designed GUI and the basic evaluation condition for the drawings would be the correct building elements extruded onto the 3D BIM model.

The target to reduce the time consumed by the conversion process of this proposed methodology is one of the test criteria as it would compare the manual method of converting 2D CAD floor plan by slowly redesigning into the Autodesk Revit with the Autodesk Revit tools and the automated approach of using a designed GUI to run API concept to generate the BIM model. In terms of data extraction of information from the CAD drawings, the manual approach is implemented by drawing it traditionally. Hence, the amount of time needed for redrawing the floor plans is taken in consideration to the total time for manual approach as the data extraction process assumed to be the same as redrawing process.

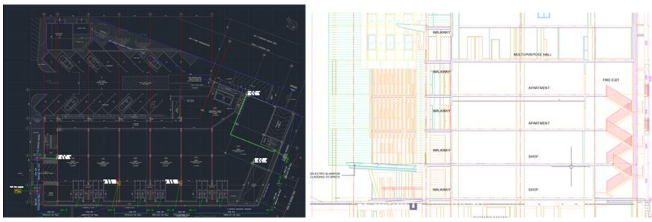


Fig. 13 *Floor Plan and Elevation Plan for Lamunin Building*

The floorplan utilized for the Lamunin building visualization is based on the Fig. 13 shown above. Running both manual and automated approaches to generate the 3D BIM model, the comparison of the result is seen on Fig. 14 and Fig. 15 below. The machine learning model being able to process the data provided into the final 3D BIM model is conducted through the developed GUI as well illustrated by Fig. 12.

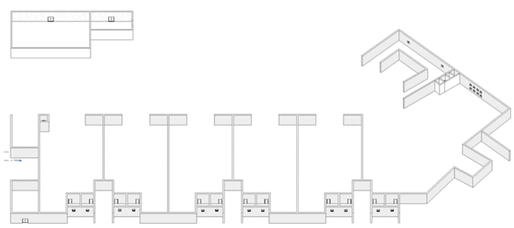


Fig. 14 *Visualized 3D BIM Model with Manual Approach*

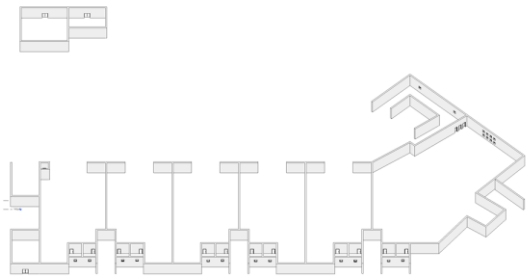


Fig. 15 *Visualized 3D BIM Model with Proposed Automated Approach*

Differences between manual and automated approach have been indicated in the summary table shown on Table VI has been compiled. For a user with not a lot of experience for drawing architectural plans with the 3D modelling tools on the specific complex building plan provided for testing purposes, it would take an hour and 27 minutes. On the other hand, it would take 2 minute and 15 seconds for the automated process proposed despite showing signs of errors in smaller diagonal walls not classified properly by the neural network which suggests that the system designed may have rooms for improvement. Despite the error, the automated process was still able to reduce time consumed significantly which portrays the benefit of this system in terms of reliability and usefulness for users.

Table.5: *Comparison between Manual and Automated Visualization Process to 3D BIM Model*

Process	Manual	Automated
Time taken	1hr 27min	2min 15s
Building element count	115/115	112/115
Accuracy of quality based on resemblance	Medium	Low

Besides the Lamunin building, other datasets that are in simpler complexity were provided to the same machine learning model to run classification and the resulting visual aid has shown below including elevation of wall elements and how some wall elements may be shorter than other.

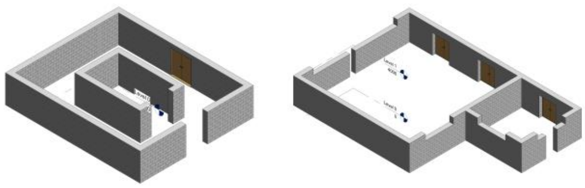


Fig. 16 *Other two buildings derived from system developed*

The tabulation of total counts of all the different building drawings in a single diagram in the form of stacked bar graph is indicated on Fig. 17. With a simple layout such as the Genset building it was found that the system does not produce any errors which bears the fruit of success on the logic designed for the algorithm as indicated from having same data count for both classified data and visualized data. In terms of a moderate drawing, a smaller error was observed at one of the corners of the building where the building was not completed so the count was referred as one less since the building wall length was not expected length. With the complex design on the Lamunin building and having large number of external components, the best result has provided only 3 errors in the count only. Since the machine learning model is utilized for classification purposes, it is not perfect as it may require more intelligent classification through better neural networks or more training data. However, the errors are not that major so users can edit the remaining mistakes easily with Autodesk Revit that does not take up too much time.

With that, the automated process shows a clear success from the different tests and the concluding statement would be the higher the complexity of a CAD drawing provided, the harder the visualization process would be able to reproduce the most accurate and precise BIM model.

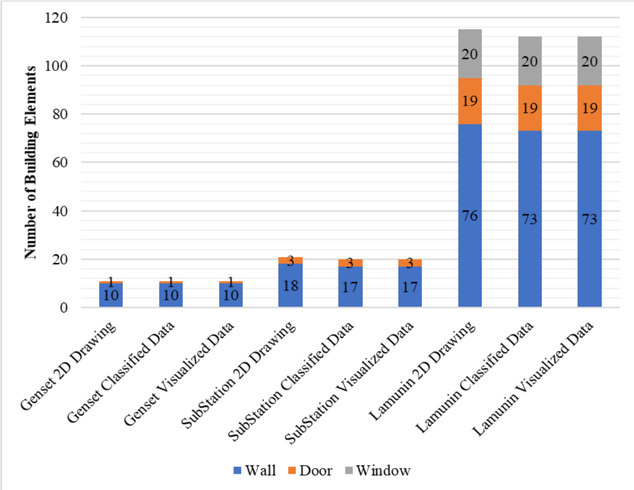


Fig. 17 *Graphical Tabulation for overall building element identification by machine learning model developed*

Discussion on Project

During the project development, a lot of different factors were contributing to the restrictions towards completing the project within the initial timeline. Some of these restrictions is referred as the limitations of the project so it would suggest that the project is incomplete because further functions or features can influence the effectiveness to the entire system.

Self-understanding is conducted of how the CAD drawings are interpreted as a set of information numerically for the machine learning model to understand. In typical literature papers, the building elements for considerations are walls, windows, and doors. Besides the addition of diagonal wall elements in the system, there are so many other elements that can be included as the BIM model. The Lamunin building floorplan denotes the numerous amounts of information suggesting the other possible building elements such as sewerage system, electrical layout, stairs, and others. Another limitation of the project is on the CAD drawing analysis where there are different types of doors and windows or even curved walls that may not be identified on the current system. This shows that the system right now is purely object sensitive in terms of available inputs.

On the other note, the predictive model was design in a simple manner so the main limitations would relate to the minimal number of conditional requirements included. Multiple variables can be input into the linear regression model for analytical process which may change the output analysis result. In the current system design, it would only be able to denote the heat regions based on two simple variables which lowers the accuracy. By allowing the predictive model to display the results on the Autodesk Revit is not possible in current system design to ensure that only a single software can be used to view the results which is part of the limitations of the project.

The option to reconstruct the other building elements are not available in the system as it focuses on the 3 main and common building elements. Currently, the inclusion of BIM data relating to different systems in the building design such as electrical layout is a limitation as it would require connectivity of such data directly working with the designed GUI for visualization process. The side limitations would be only the specific door type and window type is set into the system which means that whenever a larger door or longer door drawing is fitted as inputs, it would still visualization the standard single hinge room as BIM model.

The project can be improved in the future to remove the limitations with some specific actions. With the machine learning model being at 85.9701% level of accuracy, it would be able to improve by providing more completed datasets with other building elements not considered or exchanging the neural network with a different type to find better suitability. With the machine learning technology improving in the market at a steady pace, a specialized network design in the future may be able to satisfy the requirements of this type of system. On top of that, the predictive model can be designed with other network models such as logistic regression, ridge regression, time series or even decision trees so that a better accuracy model can be found.

By inclusion of other building elements can build up the complexity of the BIM model which makes it more informative as well. On top of that, the floor plan on Lamunin building is a multi-floor building so the future projects can be designed by reading more than a single floor to visualize the entire skyscraper like building. Changes in the different ways CAD drawings can differ in companies, it would be part of consideration to use deep learning to allow more types of drawing type structures to be read. Another possible method that can solve this issue would be to have a specialized project on simply converting any CAD drawings into a typical standard version that can be fed into the machine learning model for classification.

As shown by including predictive maintenance model to the project, it shows the adaptability of the project to be expanded into other concepts such as incorporating Augmented Reality, Virtual Reality, or the latest Mixed Reality to show the model in a different view than Autodesk Revit environment. The entire coding file utilized to develop the proposed system would be ideal to read directly by the Autodesk Revit API instead of currently being read on an external code environment. Hence, it would be able to simplify the entire coding as a single Python script file on Pyrevit to have all input files selection, visualizing of the BIM model and the predictive maintenance analysis can be carried out with a single button on Autodesk Revit only.

Conclusion

In conclusion, the article has shown a good degree of success in aligned with the objectives of the project from the results generated from this system on automated visualization of 3D BIM model from a 2D CAD drawing from the usage of machine learning and inclusion of a predictive model as well. Every one of the objectives was satisfied accordingly from the design of this project. Different functionalities on the two machine learning models are configured appropriately with a self-designed GUI to cater to the operations of this system relates to the second objective of this project for having a user-friendly application. Evaluation criteria lies greatly on the machine learning model performance as without it, the project methodology does not exist.

The first task of the project involves the data extraction code to differentiate between the different informations made available from the 2D CAD drawing to be compiled into a proper dataset. By utilizing a simple FFNN model for feature classification, it was developed to identify the three main building elements denoted in this project which are walls, doors, and windows. During the development phases of the project, a new feature for diagonal wall detection was included as the 2D CAD drawing provided by Jurusy Perunding Sdn. Bhd. bears diagonal walls which cannot be determined with the initial proposed logic approach. Training and validation phases for accuracy and loss factors was measured from the machine learning neural network for the proper tabulation of results. The number of predicted building elements that was visualized into Autodesk Revit indicates the reliability of the overall system. Upon completion of the classification of information from the extracted information file provided, an Autodesk Revit API known as Pyrevit was implemented to read the file extracted in terms of Python script to generate the wall, window, and door elements onto the Autodesk Revit interface. The concluding results have achieved an average accuracy of 85.9710% from the CAD drawings provided as a proper illustration of the 3D BIM model building.

While the main component of the project completes, the small-scale predictive maintenance model designed with a linear regression predictive machine learning model was able to portray a direct analysis of the heat regions in the building plan. A set of simulation data collected to replicate the BIM building data aspect was inserted into this model for the predictive outputs. Some of the major factors for this analysis is the comfort temperature and steady heat loss values in the few rooms in the Lamunin building. The results denote the highest heat region rooms on the status panel designed on the GUI and exported a csv file. The GUI was designed in such a manner that users can input necessary files to the project's overall system and output the classified BIM data files fed into Autodesk Revit with a click of a button. The entire process works on the backend which has shown the user a 3D BIM model and predictive output analysis at the end of the process.

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