ICCEPM 2024 https://dx.doi.org/10.6106/ICCEPM.2024.0973
The 10th International Conference on Construction Engineering and Project Management
Jul. 29-Aug.1, 2024, Sapporo

Mixed-input neural networks for daylight prediction

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Abstract: In this research, we present the implementation of a mixed-input neural network for daylight prediction in the architectural design process. This approach harnesses the advantages of both image and numerical inputs to construct a robust neural network model. The hybrid model consists of two branches, each handling in-depth information about the building. Consequently, this model can effectively accommodate a wide range of building layouts, incorporating additional information for enhanced predictions. The building data was created utilizing PlanFinder in Rhino Grasshopper, while simulation data were generated using Honeybee and Ladybug. Weather data were collected from three distinct localities in Vietnam: Ha Noi, Da Nang, and Ho Chi Minh City. The neural network demonstrates outstanding performance, achieving an R-squared (R2) value of 0.95 and the overall percentage difference in the testing dataset ranges from 0 to 20.7%.

Keywords: Convolutional neural network, Daylight analysis, Mixed-input neural network, Multilayer perceptrons

1. INTRODUCTION

In recent years, artificial intelligence (AI) has significantly reduced the time-consuming and complex simulation tasks related to daylight analysis in architecture design[1], [2], [3]. It has decreased reliance on simulation tools and accelerated workflow processes [4], [5].

The selection of an AI model is contingent upon the intended prediction objective and the nature of the data it handles. Most of the issues related to predicted daylight analysis pertain to regression problems. Liu et al, (2023) determined that the Artificial Neural Network (ANN) is the optimal model for regression tasks [2]. Ayoub (2020) stated that more than 50% of the models used are ANN, with the rest being comprised of Multiple Linear Regression (MLR), Support Vector Machines (SVM), and Decision Trees (DT) [6].

Among research that used ANN for prediction, many used multilayer perceptrons (MLP) when dealing with numerical data input [4], [5], [7], [8]. The numerical data could be the parameters that characterize the building shape like room size, window-to-wall ratio, building orientation, sensor point identification, sensor relationship with surrounding obstacles, building location, weather data, material properties… Conversely, in cases where the input data is in the form of images, other researchers, such as He et al. (2021), have opted for the Convolutional Neural Network (CNN) and GAN (Generative Adversarial Network) architecture [9]. In this case, the building's 2D-floor plans were used as the input data for the neural network.

The drawback of utilizing numerical data as input arises from its incapacity to fully depict the intricate forms of buildings, rendering it less optimal for handling varied building layouts. Conversely, image input can compensate for this limitation by visually representing the building's form. However, a limitation with image input is that numerous parameters associated with the buildings or the design context may not be readily depicted or represented via an image.

From this perspective, the study presents a method that utilizes a hybrid approach called a mixed-input neural network. This network exploits the advantages of both types of inputs. The mixed-input neural network consists of two branches for data input: one dedicated to processing images using CNN and another designed for handling numerical data using MLP. With this approach, the neural network can handle various diverse building layouts while incorporating additional information.

This study's building and simulation data were produced through an automated process in Rhino and Grasshopper, employing the Honeybee and Ladybug simulation tools. The training process was carried out on Google Colab, yielding very positive prediction results from the model. The subsequent sections provide comprehensive information on the research methodology, evaluation, and conclusions.

2. METHODOLOGY

2.1 Overall workflow

Figure 1 illustrates the comprehensive workflow of this research, which consists of three primary parts: data preprocessing, neural network training, and utilization of the well-trained model for predictions. The first step involves data preparation for training the mixed-input neural network, which includes integrating image and non-image data and simulation data. The next step involves data processing and training the neural network. In this phase, the prepared dataset, comprising both image and non-image data along with simulation data, undergoes further processing to ensure compatibility with the neural network architecture. Once the mixed-input neural network is well-trained, it is utilized for predictions with appropriate input data.

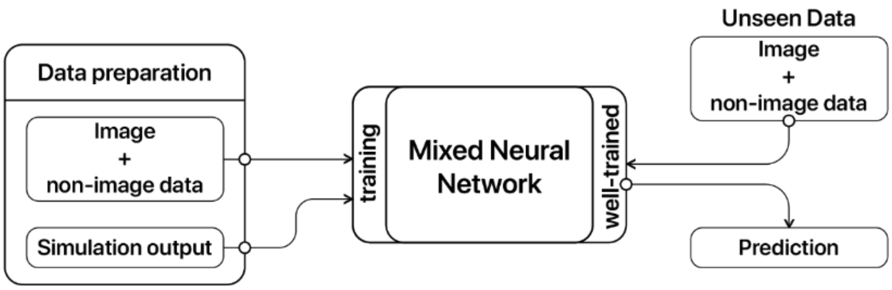


Figure 1. The overall workflow

2.2 Data preparation

The building and daylight simulation data for this study were generated using Rhino and Grasshopper, utilizing the PlanFinder, an AI-based tool for generating floor plans, alongside Ladybug and HoneyBee simulations [10]. The dataset used encompasses floor plans tailored for individual houses, spanning an average size spectrum from 50 m^2 to 100 m^2. These floor plans replicated real-world designs and offer a variety of layouts and room quantities. By integrating these floor plans, the practicality of the study was enhanced.

PlanFinder generates a floor plan based on a boundary and an entrance point. A rectangle with sides A and B, ranging from 7 m to 10 m, was established, accompanied by the entrance point *(x)* moving along one of its edges, as shown in **Figure 2**. Although PlanFinder can efficiently generate floor plans, it cannot currently adjust the window-to-wall ratio *(W)*. As a result, a custom script has been implemented to modify the window-to-wall ratio between 0.7 and 0.9, as shown in **Table 1**. After obtaining the floor plans, the next step was to prepare energy models for the simulation process.

Table 1. Input parameters

Parameters	Number of values	Values
Width (A)	7	{7 m to 10 m | step = 0.5 m}
Height (B)	7	{7 m to 10 m | step = 0.5 m}
Entrance (x)	3	0.25, 0.5, 0.75
Window to wall ratio (W)	3	0.7, 0.8, 0.9
Location (L)	3	Ha Noi, Da Nang, Ho Chi Minh
Orientation (O)	4	0, 90, 180, 270

For daylight analysis, this research used the Spatial Daylight Autonomy (sDA) metric, which indicates the percentage of the analysis area that meets a minimum daylight illuminance level during a specified portion of the annual operating hours. The standard sDA thresholds are 300 lux of illuminance and 50%-time fraction (sDA300, 50%) [11]. The simulation process was carried out at three distinct locations in Vietnam, ranging from North to South: Hanoi, Da Nang, and Ho Chi Minh City, with the corresponding weather data. **Table 1** shows that each case was considered with various building orientations *(L),* including North, South, East, and West. The working plane was set up at a height of 0.76 m, with a grid size of 0.3 x 0.3 m. For the sake of simplicity, all materials were assigned default settings. The entire process, from creating floor plans to collecting simulation results, was automated using Grasshopper.

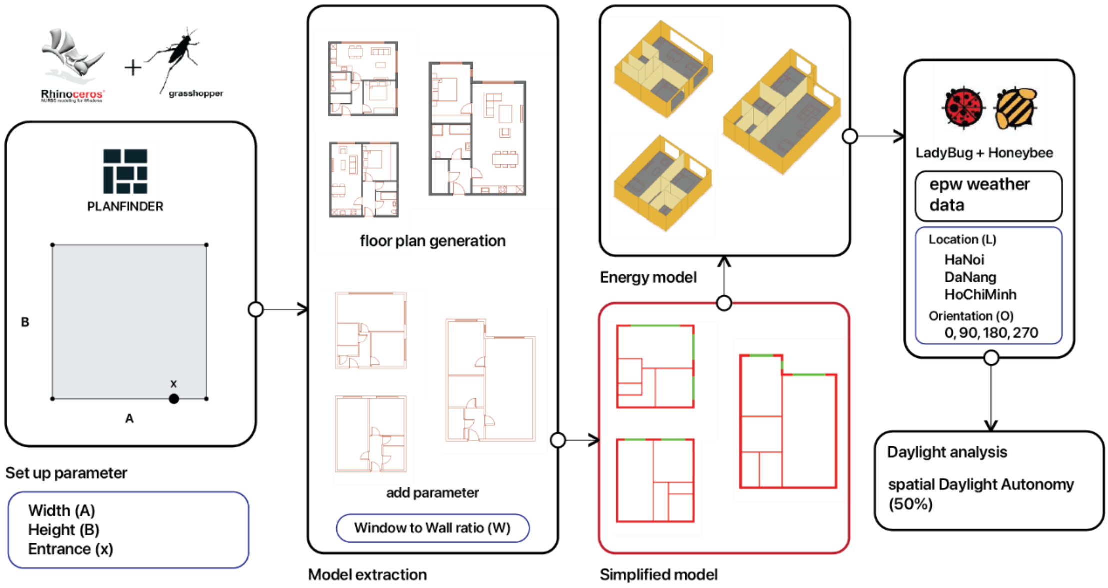


Figure 2. Data preparation process

Upon completing the entire simulation process, all input and output data were collected. In summary, the input data in image form includes simplified floor plans of the energy model, as shown in **Figure 2**. The numerical input data consists of a collection of parameters, including *A, B, x, W, L,* and *O*. The output data comprises sDA values for each case. Initially, the dataset contained 5,292 cases. However, after removing some unfavorable cases, the remaining dataset contains 5,040 cases.

2.3 Mixed-input neural network

As described in **Figure 3**, the mixed-input neural network combines CNN and MLP models to make predictions. The input data is separated into two branches: the image branch, which feeds into the CNN, and the numerical data branch, which feeds into the MLP. Instead of producing separate final results, their outputs are concatenated in the last layer of both models. The concatenated output is then passed through fully connected layers with specific activation functions to generate predictions.

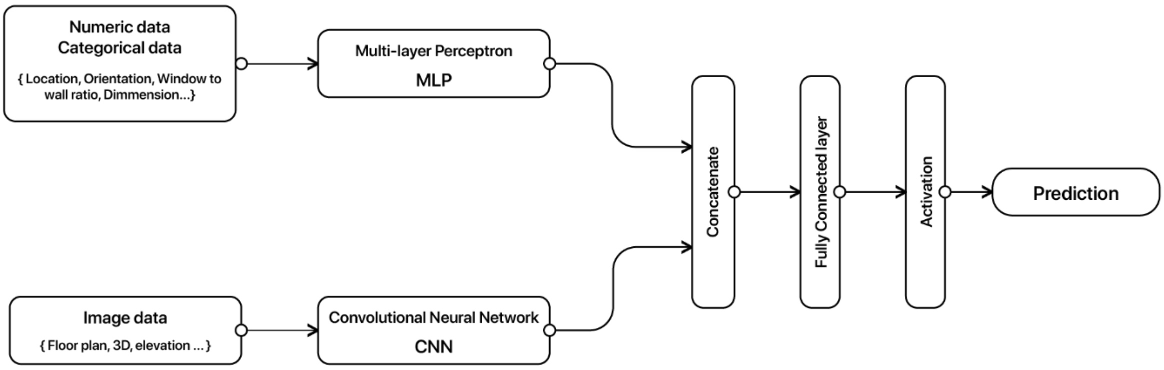


Figure 3. Mixed neural network data flow

The data was preprocessed to get ready for neural network training. Initially, the image data was uniformly resized to 680 x 680 pixels. A min-max scaling approach was used to normalize each parameter of the numerical data. This technique ensures that all parameters are within the range of 0 to 1, regardless of their original unit formats. Furthermore, the location data was encoded using numerical values, with values ranging from 0 to 2 assigned to the three cities, before being scaled. The dataset was split into a training set and a test set with a ratio of 75-25, following **Figure 4**. In addition, 20% of the data from the training set was allocated as a validation set.

The neural network was trained on Google Colab using Tensorflow version 2.15.0. Referencing **Table 2**, the MLP branch of the model incorporates an input layer designed for numerical features, configured with a size of 6 to align with the training data. Subsequent hidden layers consist of a dense layer with 6 neurons and Rectified Linear Unit (ReLU) activation, followed by another dense layer with 4 neurons and ReLU activation.

Table 2. Mixed Neural Network Architecture

Model Branch	Layer type	Details
MLP	Input layer	Numerical feature, dimension: 6
	Hidden layer 1	Dense layer (6 neurons) and ReLU activation
	Output layer	Dense layer (4 neurons) and ReLU activation
CNN	Input layer	Image (128x128x3)
	Convolutional layer	Three layers with filter (16, 32, 64), each with ReLU activation, batch normalization, and max-pooling
	Fully connected layer	Flatten, Dense Layer (16 neurons), with ReLU activation, batch normalization, and drop-out.
	Output layer	Dense layer (4 neurons) with ReLU activation
Combined Model	Merge MLP and CNN	Concatenate MLP and CNN outputs
	Fully Connected Layer	Dense layer (4 neurons) with ReLU activation
	Output Layer	Dense layer (1 neuron) with linear activation for regression (sDA)

Conversely, the CNN component is specialized for processing image data, accepting images with dimensions of 128 x 128 x 3 (height, width, depth). The architecture comprises three convolutional layers with increasing filter sizes (16, 32, 64), each featuring ReLU activation, batch normalization, and max-pooling. A fully connected layer follows, flattening the volume and connecting to a dense layer with 16 neurons, ReLU activation, batch normalization, and Drop-out. The output layer consists of a dense layer that contains 4 neurons and utilizes the ReLU activation function.

The outputs of both the MLP and CNN models are amalgamated into a single input for the final layers. The ultimate layers include a fully connected layer head with two dense layers. The last dense layer operates as the regression head, predicting the Spatial Daylight Autonomy (sDA).

The neural network's hyperparameters were set with a learning rate of 1e-4 and the Adam optimizer, while the batch size was set to 64. The selected loss function for training was the mean squared error (MSE). The Early Stopping technique was utilized to mitigate overfitting and improve the ability of the model to generalize. This involved monitoring the validation loss and stopping the training process if no improvement was observed for a continuous period of 100 epochs. The model's performance was validated using the coefficients of determination (R^2) and mean absolute error (MAE) [12]. Equations (1) (2) describe the following metrics:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i| \tag{1}$$

$$R^2 = 1 - \frac{\Sigma_{i=1}^{N}(\hat{y}_i - y_i)^2}{\Sigma_{i=1}^{N}(y_i - \bar{y}_i)^2} \tag{2}$$

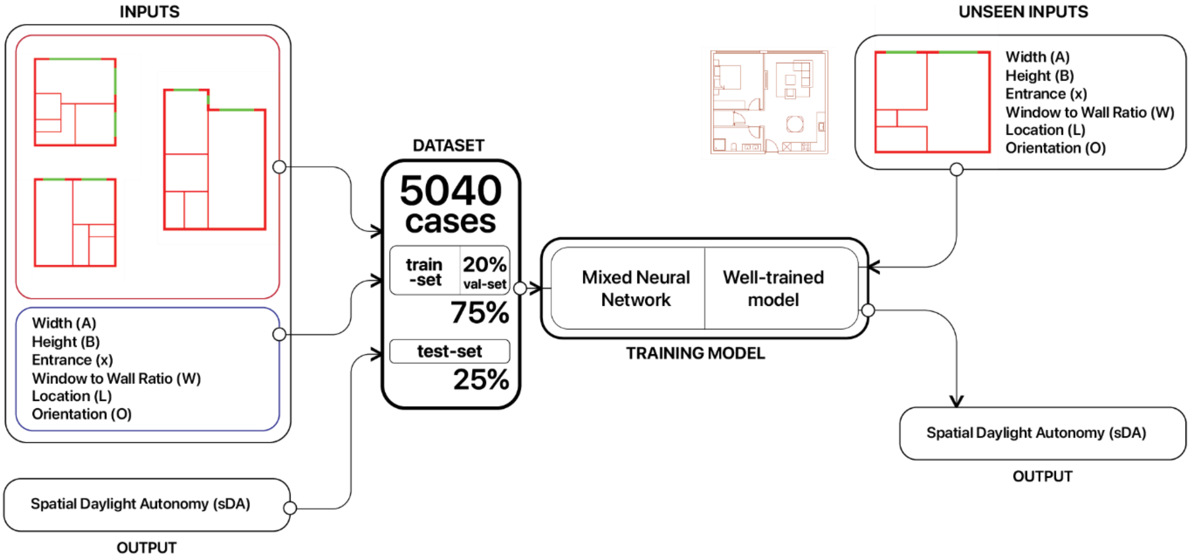


Figure 4. Input and output for training and predicting

3. RESULTS

Thanks to the Early Stopping function, the training process was halted at epoch 595. The model exhibited the following key metrics: the Training Loss was 6.3629e-04, and the Validation Loss was 4.5592e-04, as illustrated in **Figure 5**.

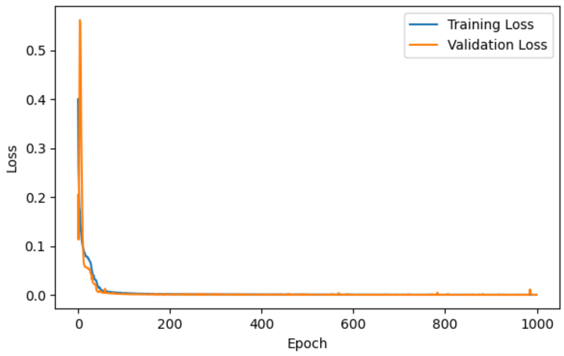


Figure 5. Training and Validation loss over Epochs

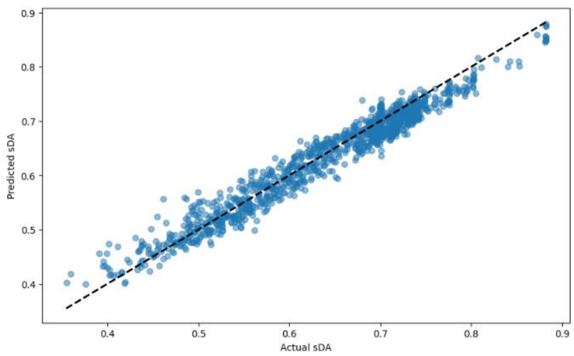
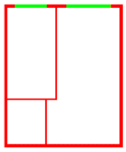
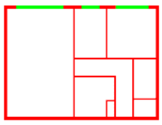
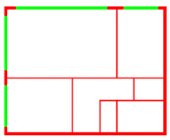
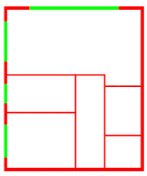
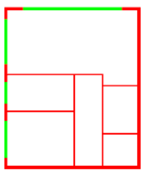


Figure 6. Actual vs. Predicted sDA values

Upon applying the prediction model to the test dataset, remarkable accuracy was observed, evidenced by the R^2 value of 0.95 and the MAE of 0.02. Illustrated in **Figure 6**, the majority of predicted points closely align with the 1:1 line, indicating a high level of agreement between the model's predictions and the actual values. The absolute percentage difference (%) range across the entire testing dataset is from 0 to 20.7%. **Table 3** provides a detailed comparison of several cases, offering a granular examination of how the model's predictions compare to the actual values across different instances.

Table 3. A comparison of several cases of actual and predicted sDA.

Case number/ image	Input						Output		Absolute Percentage Difference (%)
	Location (L)	W/W ratio (W)	A	B	Orientation (O)	Entrance (x)	Actual sDA	Predicted sDA	
4350 	Da Nang	0.8	7 m	8.5 m	270 (East)	0.5	0.503	0.536	6.62
240 	Ha Noi	0.8	9.5 m	7.5 m	0 (North)	0.75	0.567	0.567	0.06
1666 	Ha Noi	0.9	10 m	8 m	90 (West)	0.5	0.742	0.726	2.16
915 	Ho Chi Minh city	0.7	8.5 m	10 m	0 (North)	0.5	0.709	0.69	3.34
3576 	Ho Chi Minh city	0.8	8.5 m	10 m	180 (South)	0.75	0.734	0.724	1.33

4. CONCLUSIONS AND FUTURE WORK

The research article introduces a method for predicting daylight performance using a mixed-input neural network. By incorporating both image and non-image contextual information, the neural network model demonstrates the capability to predict daylight performance rapidly. The model's exceptionally accurate predictions substantiate the promise of this approach, highlighting its potential as an effective and reliable tool in daylight performance prediction.

Although the model performed well with the current dataset, the general characteristics of the floor plans in this dataset were not yet truly diverse. Rectangular boundaries still be used to generate them, and the sizes were not significant. Furthermore, many non-geometric features, such as material types, shading devices, etc., were not addressed. Due to its simplicity, the simulation setting was also set by default. Therefore, in the subsequent steps to advance this research, a more extensive dataset with diverse non-geometric information needs to be incorporated. Additionally, the method can be extended to predict various metrics such as energy usage and lighting indices like annual sunlight exposure, illumination, and daylight factor.

Furthermore, this research can develop into a tool for the design process, seamlessly incorporated into the output of PlanFinder. As a result, it can immediately offer real-time evaluations of a project's daylight or energy consumption once PlanFinder produces it. This integration would allow designers to promptly obtain insights into a structure's daylight performance or energy efficiency, thereby improving the efficiency and effectiveness of the design workflow.

ACKNOWLEDGMENTS

This work is financially supported by Korea Ministry of Land, Infrastructure and Transport (MOLIT) as Innovative Talent Education Program for Smart City and supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2022R1A2C1010759).

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