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A novel machine learning-based framework for mapping outdoor thermal comfort

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ABSTRACT

Rapid urbanization and global warming have increased heat stress in urban areas. This in turn makes using indoor space more compelling and leads to more energy consumption. Therefore, paying attention to outdoor spaces design with thermal comfort in mind becomes more important since outdoor spaces can host a variety of activities. This research aims to introduce a machine learning-based framework to predict the effects of different urban configurations (i.e. different greening configurations and types, different façade materials, and different urban geometry) on outdoor thermal comfort through training a pix2pix Convolutional generative adversarial network (cGAN) model. For the training of the machine learning model, a dataset consisting of 208 coupled pictures of input and output has been created. The simulation of this data has been carried out by ENVI-met. The resulting machine learning model had a Structural Similarity Index (SSIM) of 96% on the test dataset with the highest SSIM of 97.08 and lowest of 94.43 which shows the high accuracy of the model and it could have reached an answer in 3 s compared to the 30-min average time for ENVI-met simulation. The resulting model shows great promise for assisting researchers and urban designers in studying existing urban contexts or planning new developments.

HIGHLIGHTS

- Machine learning use in outdoor thermal comfort assessment has been investigated.
- Vegetation, urban geometry, surface albedo, and water bodies have been studied parameters.
- Vegetation and street orientation have the highest and water bodies have the least impact on outdoor thermal comfort.
- Pix2pix algorithm implementation could create thermal comfort maps with 96% SSIM.

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1. Introduction

More than half of the world's population lives in urban areas which are constantly growing in favour of urbanism and reaching 79% of the population in developing countries (Population Reference Bureau, 2022). The development of cities and lack of attention to open space planning deeply affects the urban microclimate (Dugord et al., 2014). The Urban Heat Island (UHI) leads to an increase in the air temperature affecting the people's comfort and health conditions (Buchin et al., 2016) and buildings' energy demand.

Physical urban parameters including urban geometry, vegetation, surface albedo, anthropogenic heat, and water bodies directly impact environmental parameters(e.g. solar radiation, wind speed, air temperature, and air humidity) which affect the urban thermal environment and have been vastly studied in different climate contexts by field measurements and simulations (Lai et al., 2019). Based on, Physiologically Equivalent Temperature (PET), Predicted Mean Vote (PMV), Universal Thermal Climate Index (UTCI), and Standard Effective Temperature (SET*) are the four most commonly used thermal comfort indicators in urban thermal evaluations (Lai et al., 2020).

Compact urban spaces with a low sky view factor (SVF) or high height-to-width ratio (H/W) are characterized by reduced exposure to solar radiation (Abdollahzadeh & Biloria, 2021). Many studies such as the study done by Wang and Akbari (2016) showed a positive correlation between SVF and mean radiant temperature.

Moreover, trees can affect the urban thermal environment in different ways such as reducing radiation, air temperature, wind speed, and increasing relative humidity. Although trees reduce wind speed, they still can significantly improve thermal comfort in an urban environment by reducing radiation (Colter et al., 2019; Lai et al., 2019; Lee et al., 2016). Studies that consider the cooling effects of water bodies are fewer compared to green spaces as the mitigation effects of greenery strategies are stronger than water spaces. In this regard, a meta-analysis reported that the blue spaces can provide a cooling effect of 2.5 °K on surrounding environments (Völker et al., 2013). However, their actual performance depends on the static and dynamic types of water bodies and respective fluid flow characteristics and climate parameters of surrounding areas (Aghamolaei et al., 2022).

Finally, using materials with higher albedo can result in more reflectance by surfaces in the urban environment and lower surface temperatures for these surfaces and lower air temperature, and better thermal comfort conditions (Yang et al., 2016). In a study done by Karimi et al. (2020) using ENVI-met software, researchers showed that the best strategy from the methods they considered for improving thermal comfort, is to combine low-albedo pavements, and trees with wide crowns and high trunks. However, Taleghani and Berardi (2018) reported surfaces' albedo effects on thermal comfort are much more complex, as increasing radiation as a result of reflection, on subjects' bodies can result in discomfort.

Consequently, urban design parameters could be modified in a way to help mitigate the urban heat island effect. But with so many parameters involved, it becomes obvious that analysing the urban environment is not an easy task, especially in the early design stages. It usually needs extensive knowledge of relations between these parameters and available software for modeling such matters doesn't make things any easier. Available software for urban thermal evaluations falls into two groups. The first group is limited in inputs and outputs and requires less simulation time and computation cost (e.g. Rayman and SOLWEIG). On the other hand, the second group is usually very complex and therefore needs much more input, and they are much more computationally expensive (e.g. ENVI-met, Ladybug tools, EDDY) making them less practical for non-professional users. Resolving these issues can help architects, landscape designers, and urban planners play a more active role in improving the urban thermal environment. Consequently, there is a need for tools requiring minimal inputs and short run time to assess different urban design and retrofit scenarios based on outdoor thermal comfort (OTC).

Machine Learning(ML) could be used to provide quick and accurate predictions with a small set of assumptions. A few studies have utilized ML in OTC prediction. Shah et al. showed that air temperature is the most common parameter serving as both the input parameter and focus parameter for the prediction of thermal comfort. The most common input parameters are meteorological variables relative humidity, solar radiation, and wind speed while a few studies have taken into account personal factors, such as clothing insulation and metabolic rate (Shah et al., 2022a).

Eslamirad et al. (2020) randomly modelled and simulated several urban configurations by ENVI-met. The PMV values were then used for training a linear regression machine learning algorithm (Eslamirad et al., 2020). In another study, a Support Vector Machine (SVM) method was used to predict air temperature inside courtyards in Spain as a result of meteorological data (Diz-mellado et al., 2021). Furthermore, Baghaei Daemi et al. trained a deep artificial neural network to predict the green wall performance in a short time interval, from the experimental data and a 15-day weather dataset (Baghaei et al., 2021). Finally, Shah et al. developed artificial neural network (ANN) models to predict OTC using the PET index. They used ENVI-met for thermal modeling of their studied area and found that the ANN model trained with all major meteorological variables showed the highest accuracy (Shah et al., 2022b).

Nowadays, image-to-image translation algorithms are promising since spatial thermal comfort indices are often visualized as a floorplan grid that can be represented in a pixel bitmap. The pix2pix, conditional generative adversarial networks (cGANs), can quickly generate corresponding images based on the input images encoded with information. Additionally, through an image, the designer can understand the relation between different parameters in the design and change it according to the specific needs of that context.

This algorithm has not yet been used for predicting thermal comfort in the urban environment. However, it is very prevalent in the field of predicting daylight maps. For example, research done by He et al. (2021) used pix2pix and ResNet (CNN) models for predicting annual daylight metrics maps such as sDA and UDI in different floor plan alternatives and reported that pix2pix generates visualization results close to the simulation results. They used the SSIM metric (Structural similarity index) for comparing predicted results with simulated results and found an SSIM of 0.90 for the pix2pix model (He et al., 2021). In another research, researchers used pix2pix, CycleGAN, and U-Net models for predicting wind speed in an urban setting and compared the results (Hoeiness et al., 2021).

Although currently there is no other research that used GAN models for assessing thermal comfort, Mokhtar et al. used this method in a study for pedestrian wind flow approximation (Mokhtar et al., 2020). In this study, researchers created two datasets from which the first one consisted of 800 primitive geometries of different shapes and sizes. The second dataset consisted of 225 urban configurations. They used the Open-FOAM CFD solver for simulating airflow for these datasets. Finally, after using different colour mapping techniques, the trained GAN models showed an average MAE of 0.5 m/s at pedestrian-level heights.

Therefore, this research will use the pix2pix machine learning algorithm to create a model for predicting UTCI maps in different urban contexts. In this research, the useability of machine learning algorithms and methods as tools for predicting OTC will be assessed. In addition to that, this research will try to provide a framework for future research for approaching machine learning applications in OTC research. To achieve this, the most important environmental parameters affecting OTC have been determined. Using different combinations of these parameters 208 different unique urban configurations were modelled and analysed in Tehran, Iran. The resulting dataset was used to train the pix2pix machine learning model to predict OTC maps.

2. Methodology

The study consists of two main steps. First, data generation by simulations and sensitivity analyses, second, training and validation of the pix2pix prediction model as depicted in Figure 1.

2.1. Data generation

In the first step, a dataset consisting of input and output maps needs to be created. This is achieved by modeling 208 different design alternatives in grasshopper and

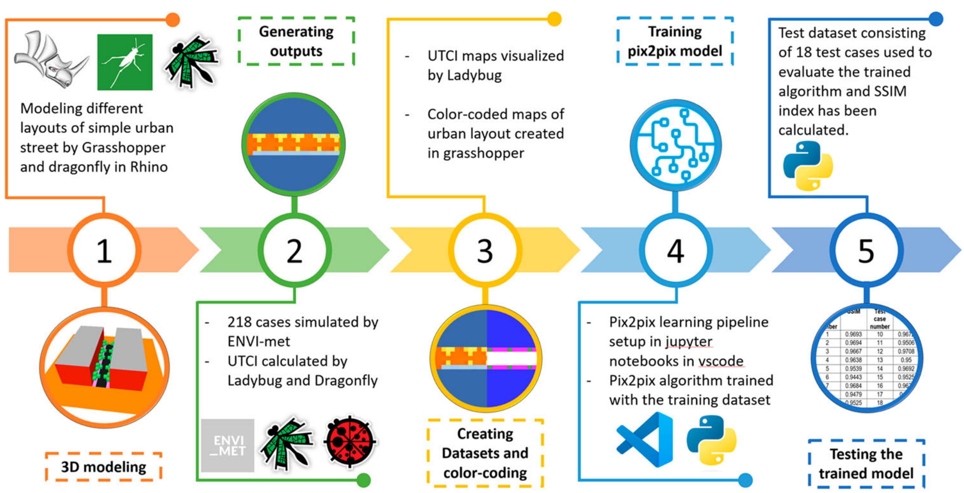


Figure 1. Research flow chart showing the process of creating datasets and training the machine learning algorithm.

then simulating thermal comfort based on the UTCI index using ENVI-met V 4.4.6 results and Ladybug plugin, on the 22 June at noon in Tehran (i.e. classified as BSk; Cold semi-arid climates based on Koppen Geiger). Due to the time-consuming ENVI-met 4.4.6 simulations (i.e. an average of 20 min for each design alternative at each 1-hour time step), a critical climate condition has been selected for data generation as in similar studies (Baghaei et al., 2021; Pezzuto et al., 2022; Ren et al., 2022). Table 1 presents the climatic condition of 22 June at noon which could result in the worst thermal comfort conditions in the urban environment in Tehran. Selecting a critical time for the simulation can give the decision makers the most insight since generally if the proposed design passes the required thresholds in that critical state it would be safe to assume that the same design would qualify in non-critical situations as well.

Although ENVI-met results have not been validated in this research by field measurements, through investigation of relevant literature it has been found that this application is a valid tool for simulating outdoor thermal environments (Aydin et al., 2019; Bande et al., 2019; Elwy et al., 2018; Liu et al., 2021). Furthermore, since this research's intentions are mainly comparative, the accuracy of the simulation tool is not the main focus and the main focus is the ability of the software to correctly show trends and changes affected by the different environmental parameters.

Design alternatives are based on four urban parameters including the urban geometry (i.e. street width and orientation, building height), vegetation (type and arrangements), façade materials (with an albedo of 0.4 and 0.9, and emissivity of 0.9 and 0.18 respectively for brick and aluminium facades), and water bodies (albedo of 0 and emissivity of 0.96). The design variables and the number of options for them which result in 432 different design alternatives are presented in Table 2. Among the total alternatives, 208 models were simulated and used for training the pix2pix model.

Due to software modeling restrictions and to get uniform input and output maps for model training, a simplified typical square-shaped urban geometry (46*46 m) in Tehran is considered. All design alternatives include a street with a length of 46 m with buildings on both sides. With 3 options for street width being 10, 14, and 22 m, building widths are set to 18, 16, and 12 m, respectively. Moreover, building heights are set to 6 and 15 m to represent low-rise and high-rise contexts.

Regarding trees, two attributes were set as variables. Firstly, the type of the trees and secondly their arrangement. Two types of trees were chosen for this study to generally represent Tehran's vegetation. The first kind were tall trees with cylindric crowns and a height of 15 m and the second type were shorter trees with spherical crowns and a height of 5 m. Also, three options were chosen for vegetation arrangements based on

Table 1. Environmental parameters in Tehran on June 22 at noon (IRN_TE_Tehran-Mehrabad.Intl.AP.407540_TMYx, 2021).

Environmental Parameters	Dry bulb Air temperature	Wind speed	Wind direction	Relative humidity
Noon 22 June Tehran	29°C	4 m/s	170° from north	23%

Table 2. Number of options for each parameter studied in this research.

	Urban context			Trees			
Parameters	Street width	Building height	Street orientation	Type	Arrangement[a]	Façade material	Water bodies
Options	10 m	6 m	North to south	tall with cylindric crow	3 (18 m space between each tree)	Brick (Albedo = 0.4 Emissivity = 0.9)	None
	14 m				5 (9 m space between each tree)		1 water body
		15 m	East to west	Short with spherical crown		Aluminium (Albedo = 0.9 Emissivity = 0.18)	
	22 m				7 (6 m space between each tree)		2 water bodies

[a]Number of trees on each side of the street.

the number of trees and the distance between them on each side as presented in Table 2. The seven tree arrangements were disregarded for the first-type trees due to the size of the trees.

Lastly, for investigating the effects of water bodies in an urban context, 3 scenarios were chosen regarding this parameter. The base option had no water bodies in it. The second option had one water body on the south side of the street in case of east-to-west streets and on the west side for north-to-south cases. Finally, the last scenario includes water bodies on both sides of the street. These water bodies were rectangular with a length of 46 m and a width of 2 m. These water bodies were intended to simulate the presence of usual water runnels parallel to the direction of the streets in Tehran.

Design scenarios are modelled in the Rhinoceros 6's Grasshopper. The Dragonfly-Legacy 0.0.04 plugin for Grasshopper is used to create the required files as inputs for ENVI-met 4.4.6. In the next step, the urban environmental parameters including temperature, wind speed, relative humidity, and mean radiant temperature are simulated by ENVI-met 4.4.6 for each design alternative. Finally, using Ladybug 1.1.0 plugin for grasshopper's UTCI calculator component and results from ENVI-met simulation (air temperature, relative humidity, MRT, and wind velocity), the UTCI indicator was calculated for every cell of the grid and the desired output map was generated. For further evaluation of the results, the mean UTCI for each case was determined.

Moreover, to assess the impact of different urban design parameters the average UTCI in each design scenario is reported compared in Figures 4–10.

2.2. Training cGAN model

Generative Adversarial Net (GAN), proposed in 2014, can generate better synthetic images than previous generative models, and since then it has become one of the most popular research areas (Leach, 2021). Through the GAN technique, an algorithm is trained to perform complex tasks through a generative process measured against a set of training images. The GAN algorithm usually consists of two neural networks. One of the networks is called Generator and the other is Discriminator.

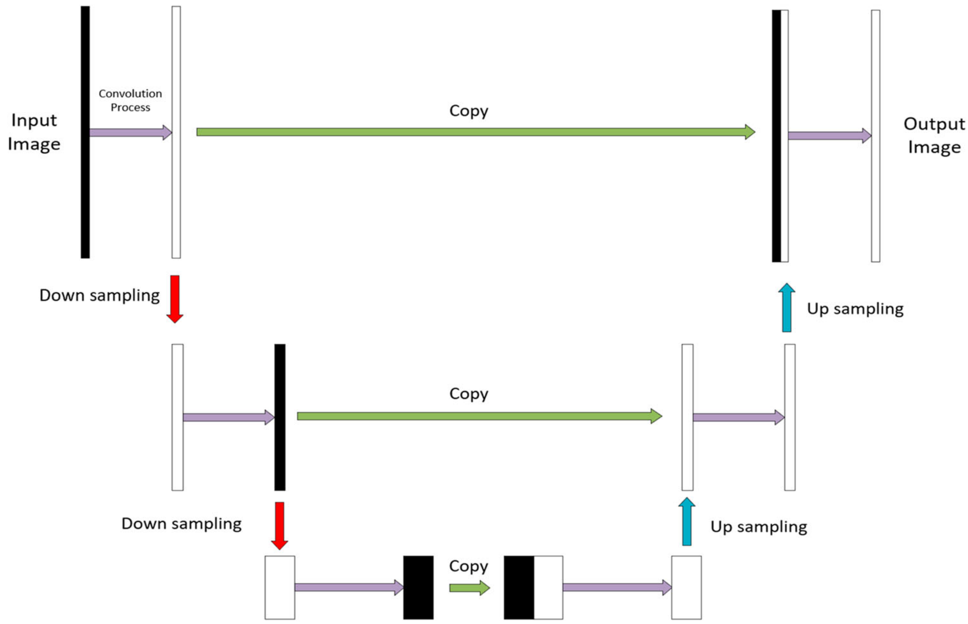


Figure 2. U-net Architecture used in the pix2pix algorithm.

In the GAN algorithm Generator network has the responsibility of creating new images given a set of input parameters (input images) and the Discriminator network tries to tell fake images (created by Generator from input data from the training set) from real images (real training data outputs). In this process, the Discriminator is trained using the real outputs, and the Generator is trained using the feedback from the Discriminator model (trying to minimize L1 loss or mean absolute error between the generated image and the target image). Crucially, the generator has no direct access to real images and is trained by receiving the error signal outputted by the Discriminator by knowing the simple ground truth that the picture is from the real stack or the Generator (Creswell et al., 2018).

Furthermore, the pix2pix algorithm is a type of conditional GAN or cGAN. In this algorithm creation of an output image is conditioned to the input, which in this case is an image. In this case, the Discriminator network is provided with both the input image and an output image (either from the Generator or the real data). The Discriminator should determine whether the output image is a plausible output of the input image or not (Brownlee, 2019). The generator network will try to create output images based on input images that can fool Discriminator to classify them as real outputs.

After generating the dataset mentioned in the last sections, the data should be prepared for the GAN algorithm. Therefore, firstly the images are resized and input and output images are coupled together. Afterward, the Discriminator is defined. The Discriminator model defined will take two concatenated images and predicts the patch output of predictions through a PatchGAN model. The model is optimized using an Adam optimizer, and a weighting is used so that updates to the model have half the usual effect as recommended by Isola et al. (2017). The sigmoid function has been used as an activation function and loss function binary cross-entropy function.

The Generator model used in this research uses an encoder–decoder based on U-net architecture. This model will first encode the input image to the bottleneck layer through several steps as downsampling as shown in Figure 2. Then the output image is generated through steps of decoding and upscaling as shown in Figure 2.

After creating the proper dataset consisting of pairs of input and output images and defining discriminator and generator functions, the training process can start. The generated dataset used for machine learning training consists of colour-coded input images in which each certain colour in the image represents a specific phenomenon as depicted in Table 3, Figure 3 and output UTCI maps. Then in a process depicted in Figure 2 as mentioned above, the input and ground truth images are downscaled and skip-connections are added between the encoding layers and the corresponding decoding layers (Navab et al., 2015). The encoder and decoder of the generator are comprised of standardized blocks of convolutional, batch normalization, dropout, and activation layers. After upscaling the predicted answer of the model the predicted image will be the result.

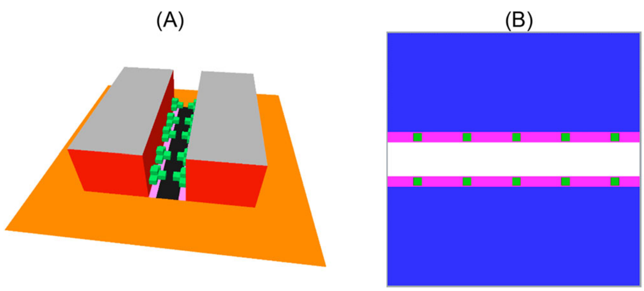


Figure 3. (A) 3D overview of a case in ENVI-met spaces. (B) Example of a colour-coded map created using Grasshopper.

The pix2pix model in this research has been developed using Keras Deep Learning Framework, and it is designed in a way that the input and output images are the size 256×256 pixels. The 70×70 PatchGAN discriminator used in this research is a CNN that performs conditional image classification. The pix2pix model was trained with a learning rate of 0.0002 and the exponential decay rate for the first moment of the gradient was equal to 0.5 for the Adam optimizer of the GAN model and 100 epochs. The training process for this model took around 24 h on a machine equipped with an intel core i7 processor and 16 GB of RAM.

2.3. Evaluating the trained model

Finally, to assess the performance of the trained algorithm, a few predicted images of the trained model should be compared to the ground truth simulated by the ENVI-met

Table 3. The reference colour coding of the generated data.

	Buildings		Vegetation		Sidewalk	Water bodies	Street (asphalt)
	Brick façade	Aluminum façade					
Low rise			Tall trees				(White)
High rise			Short trees				

application. But to have a real understanding of the accuracy of the model an indexing system is needed to be used. Generally, Mean Squared Error is used to assess the accuracy of machine learning models. However, this index is not very useful for evaluating the accuracy and similarity between images. Therefore, for this research, Structural Similarity Index (SSIM) has been used which takes two windows x and y from images by $N*N$ pixel size and computes them through the below equation:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{1}$$

With μ_x being the average of x, μ_y the average of y, σ_x^2 the variance of x, σ_y^2 the variance of y, σ_{xy} the covariance of x and y, c1 and c2 as two variables to stabilize the division with a weak denominator, L the dynamic range of the pixel values, and $k_1 = 0.01$ and $k = 0.03$ by default.

3. Simulation results and prediction models

In this section, first, the generated dataset is analysed and the impact of urban parameters on thermal comfort is discussed. Afterward, the result yielded from the machine learning process is presented.

3.1. Simulation results

The simulated dataset consisted of 208 unique design scenarios of an urban street on 22 June at noon in Tehran. In each case, one or more parameters are different from other cases as discussed in Section 3. Analysing these cases can give us insight into how changing these parameters can affect thermal comfort in this climatic context.

Different parameters regarding urban geometry in this study are street width, façade material, building height, and building orientation. In Figure 4, a significant decrease in average UTCI in high-rise cases is observed. A 1.5°C decrease is visible between high-rise cases with brick façades to low rises with the same façade material. For cases with aluminium façades, the difference between low- and high-rise cases increases to around 2.5°C. Figure 5 shows the effect of the façade material as well. It can be seen according to this graph that cases with aluminium facades on average experience around 2.5° lower UTCI. Even though a dramatic change in air temperature has not been seen in this research like research done by Fabbri et al. (2020); these results are well expected since MRT is highly influenced by the different façade materials.

Figure 6 shows two other parameters regarding urban geometry. According to data and this graph, it can be observed that with increasing street width in each step 1°C increase in UTCI is expected for east-to-west cases. This amount of change increases to 2°C for North to south cases. On the other hand, this graph shows that street orientation has a far greater effect on thermal comfort in this setup. Changing street orientation from east to west to north to south on average can result in a 2.5–3°C decrease in UTCI. These results are in line with research done by Ren et al. (2022) and Abdollahzadeh and Biloria (2021).

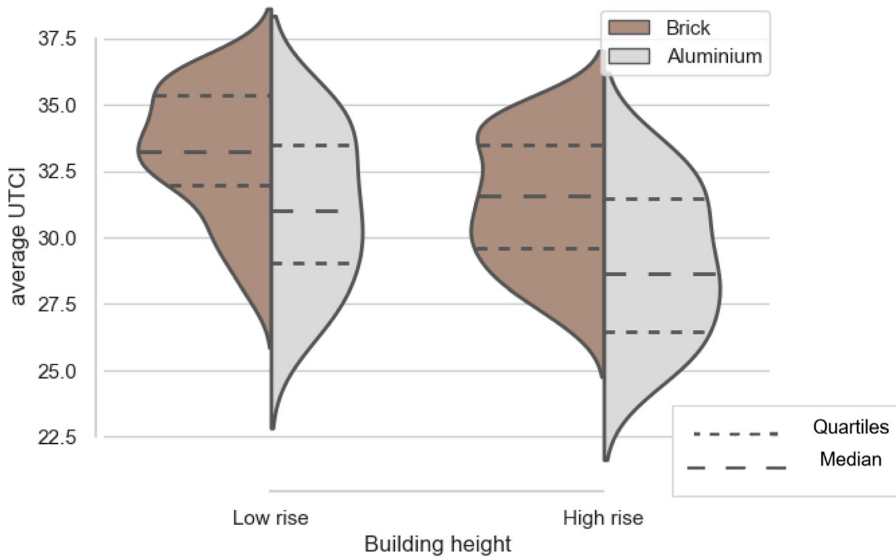


Figure 4. Average UTCI regarding building height and façade type(Note that dashed lines inside the graph show median quartiles of the data).

The last studied parameter regarding urban context is building height. Figure 7 summarizes the simulated data concerning this parameter and street orientation. It can be observed that increasing building height in the east-to-west cases on average decreases UTCI by 2°C. In north-to-south cases increasing building height results in about a 3°C decrease in average UTCI.

Based on simulation results it can be observed that the most effective parameter on thermal comfort is vegetation. Figure 8 shows how different parameters regarding

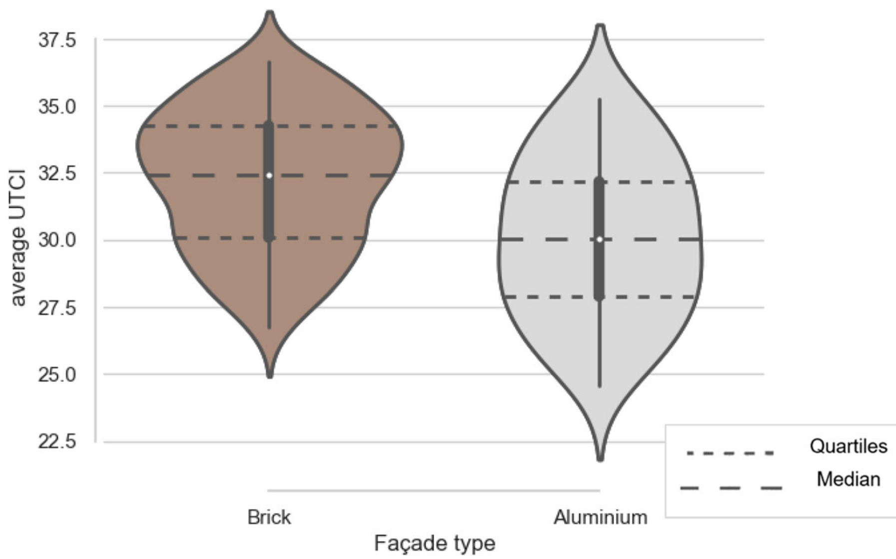


Figure 5. Average UTCI regarding façade type.

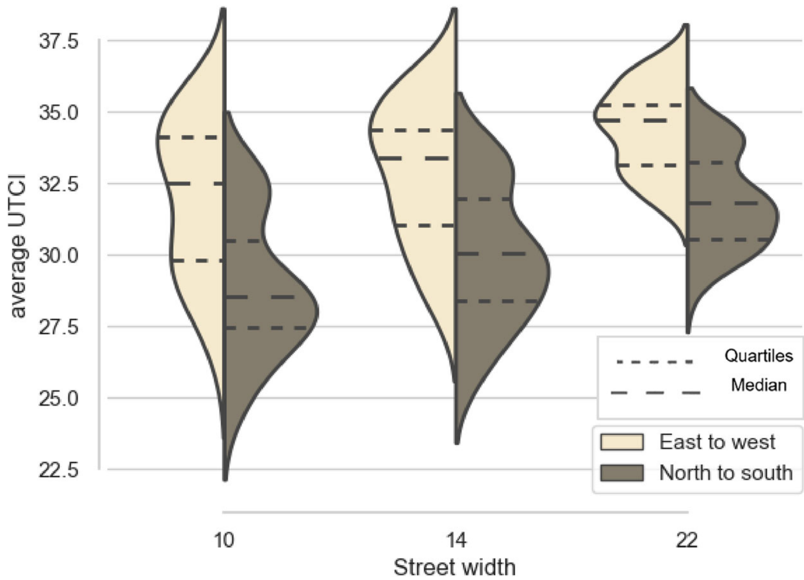


Figure 6. Average UTCI regarding street width and orientation.

vegetation affect thermal comfort. According to this figure, it can be observed that around a 2°C difference had been achieved by increasing the number of trees from 3 to 5 for type one trees. The effectiveness of this parameter, namely the number of trees is much less for type two trees where less than 2°C difference has been seen between the average of UTCI in cases with 3 and 7 trees. Another parameter that its effects can be studied is the type of trees. According to the same graph, it is obvious that changing vegetation type has a very big impact on thermal comfort. It can be

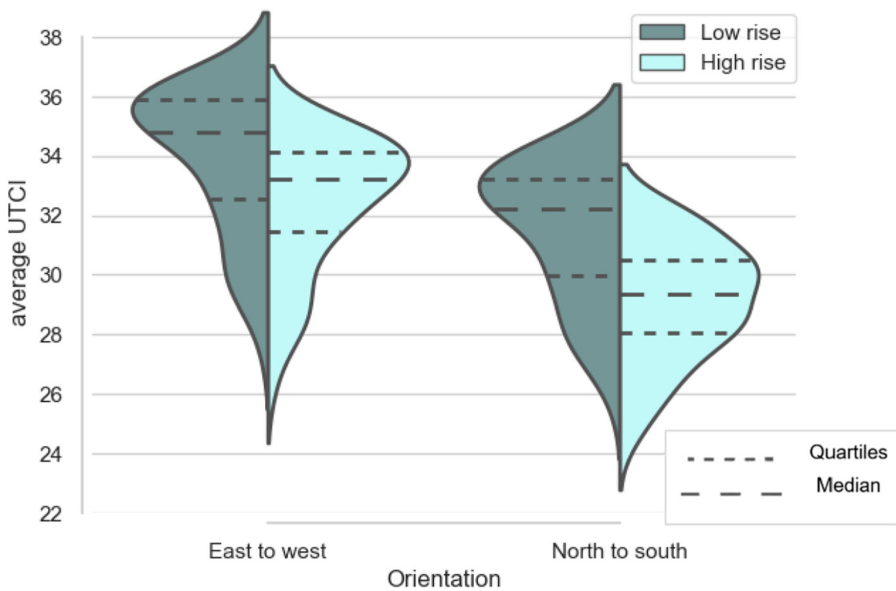


Figure 7. Average UTCI regarding cases' street orientation and building height.

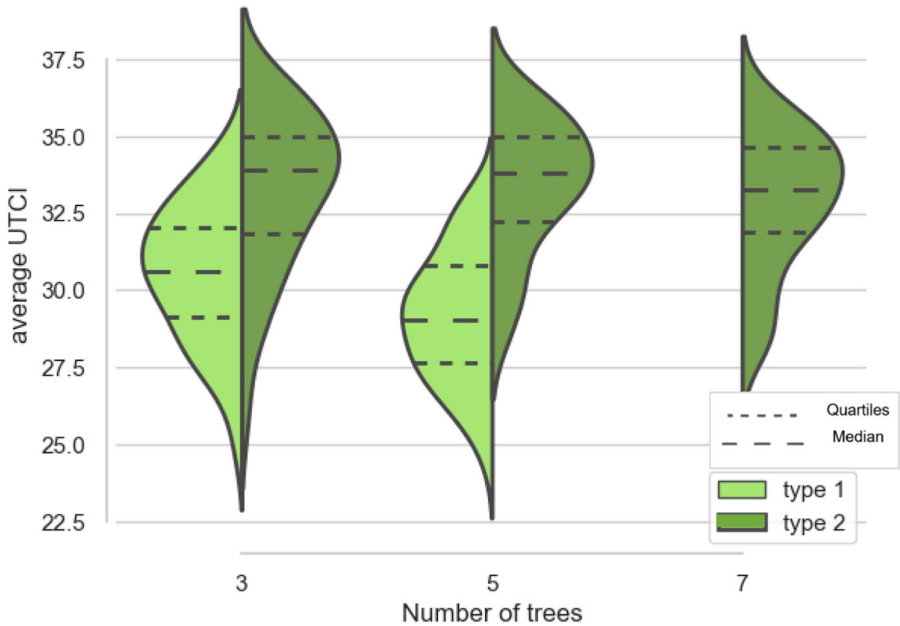


Figure 8. Average UTCI regarding the number and type of trees.

observed that the mean UTCI is around 4°C lower on average for cases with type one trees in comparison to cases with type two trees. In other research, similar results have been found. To name a few, Cheung and Jim (2018) have observed an average of 1.6–4.1°C

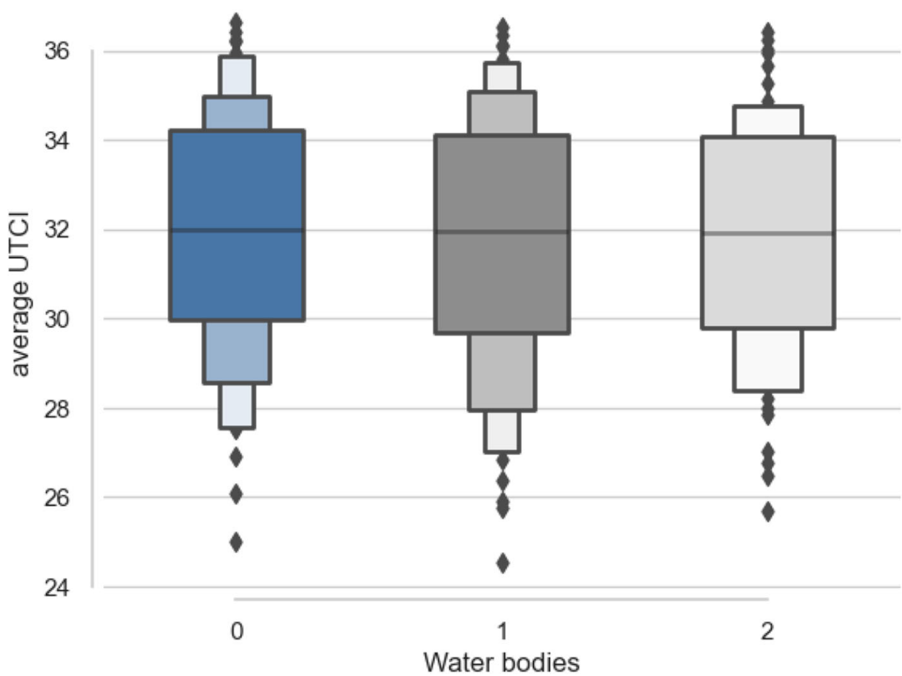


Figure 9. Average UTCI regarding water bodies configuration.

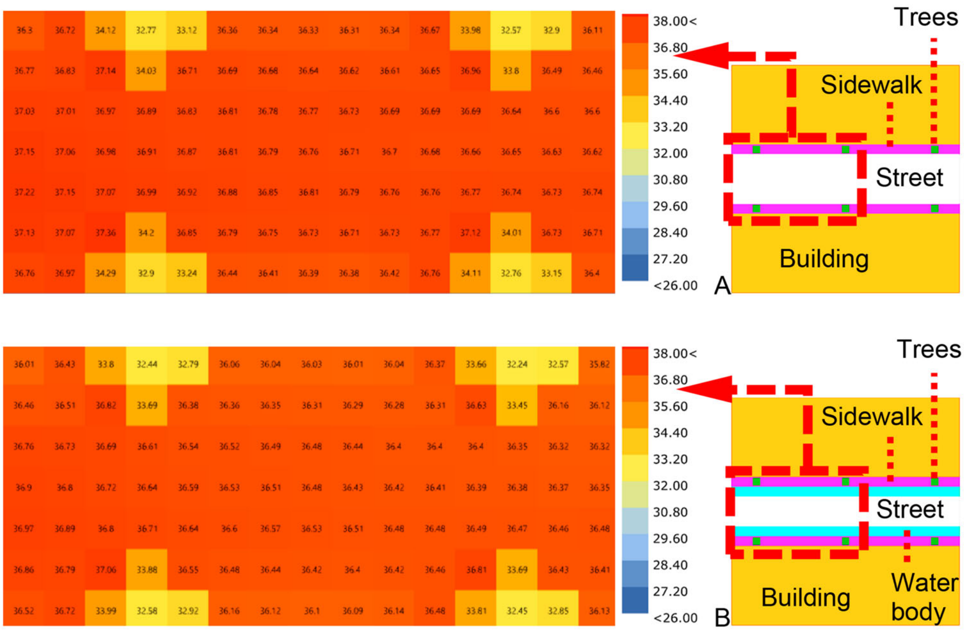


Figure 10. Two example cases. Case A has no water bodies present and case B has 2 water bodies present. A slight decrease in UTCI amounts can be seen in case B.

decrease in the UTCI index as the result of trees, and Karimi et al. (2020) have reported 2–3°C in PET index as the result of pine trees.

Among the parameters in this study, water bodies had the least effect on thermal comfort as shown in Figure 9. According to this figure, it can be observed that average values UTCI in all cases were in the same range, and also its distribution is not very different between the three scenarios. Comparing two cases shown in Figure 10 shows that having two water bodies instead of no water bodies reduced air temperature and mean radiant temperature from 36.23 to 35.95°C and 65.14 to 64.45°C, respectively. It also has increased relative humidity from 28.05 to 28.71%. However, the overall effect on thermal comfort is very small which is in line with other research findings (Liu et al., 2021; Taleghani & Berardi, 2018).

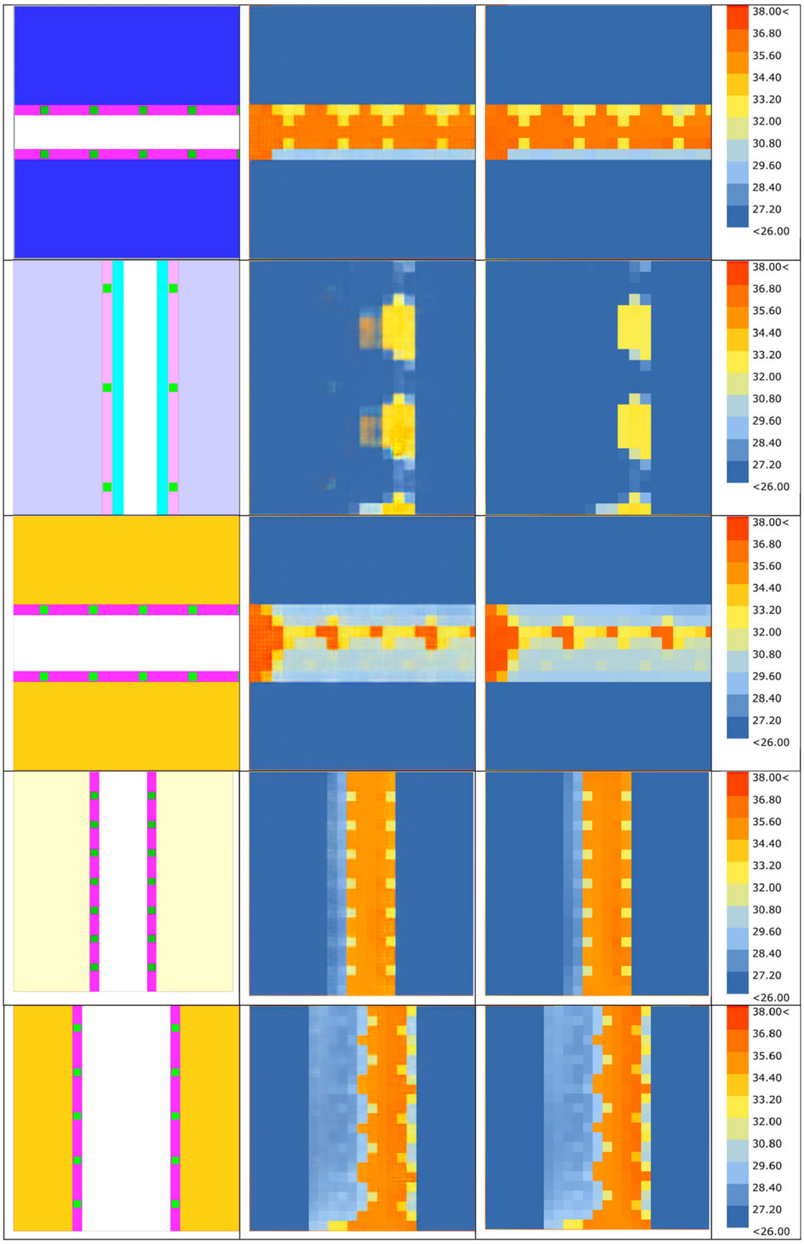
3.2. Performance of the trained GAN model

In this section, a few examples of predicted images through the trained machine learning algorithm are presented and finally, the table of calculated structural similarity index (SSIM) for all cases in the test data set is reported.

In Table 4, the five design scenarios are presented. In the machine learning process to assess the accuracy of the trained model, the training dataset and test dataset should be separate. In this way, the accuracy of the trained model can be assessed against data completely new to it, and therefore, no bias is inflicted in this process.

The first column of Table 4 shows the colour-coded input image for the trained machine learning algorithm. The second column is the predicted image, predicted by the trained model when fed by this specific input. And finally, the last column shows

Table 4. Input and output image for algorithm and simulated result.



the ground truth simulated by the ENVI-met 4.4.6 application and visualized by Ladybug in grasshopper.

By comparing these three cases visually it can be understood that the trained model is predicting results with a high accuracy that is very similar visually to the output from the simulation. In the second, a slight error can be seen at the building boundaries but other than that only difference between images is the amount of graininess. Overall, it can be said that these results can be useful to the user since there is a very small visual difference

Table 5. Structural similarity index for every case in the test dataset.

Test case number	SSIM	Test case number	SSIM
1	0.9693	10	0.9672
2	0.9694	11	0.9506
3	0.9667	12	0.9708
4	0.9638	13	0.95
5	0.9539	14	0.9692
6	0.9443	15	0.9525
7	0.9684	16	0.9679
8	0.9479	17	0.955
9	0.9525	18	0.9677

between the original and predicted images. It should also be mentioned that the simulation of these cases with ENVI-met 4.4.6 lite on a core i7 laptop took around 15 (for low-rise building cases) to 35 min (for midrise building cases). In comparison, the trained model outputs result in around 1 s.

Table 5 shows the SSIM calculated for all 18 cases of the test set. According to this table test case, number 8 has the lowest accuracy with an SSIM of 94.79. The highest accuracy achieved is for test case 2 with an accuracy of 96.94. The average accuracy for the trained model is calculated at 96.05 with a standard deviation of 0.0088.

4. Discussion and future works

In this research, a pix2pix machine learning model was successfully created. In this process, a dataset consisting of 208 cases of urban context was simulated using the ENVI-met 4.4.6 application. Although the main objective of this research was to train a machine learning model for assessing OTC, analysing the created database can also give an interesting insight into the relations between different parameters studied in this research and thermal comfort. In this section, the results of analysing the dataset and the result of the machine learning process will be discussed.

According to the results presented in section 3, it can be concluded that the most influential environmental parameters on OTC in this setup were vegetation (Cheung & Jim, 2018; Karimi et al., 2020; Xiao & Yuizono, 2022; Zeeshan et al., 2022), and street orientation (Abdollahzadeh & Biloria, 2021; Ren et al., 2022). By comparing different cases and further studying data it can be concluded that the most important factor in OTC in this context is radiation (Lai et al., 2019, 2020). This is in complete agreement with past literature demonstrating radiation as the most significant factor in OTC in summer in hot arid climates (Colter et al., 2019; Villadiego & Velay-Dabat, 2014). Therefore, street orientation and vegetation, both directly affecting total shadowed areas, are affecting thermal comfort. This can be seen also by studying the mean radiant temperature in different cases.

The least effective parameter on OTC was water bodies. This can be attributed to their small area (comparatively to the façade area for example). So as a result of their small area, their effect on radiation and their effect as heat sinks are relatively small.

Finally, by paying attention to the complete dataset of 208 cases, it could be observed that 11 cases had an average UTCI between 24.5 and 26.9°C which is no thermal stress zone for UTCI, and 96 cases had an average UTCI between 27–32°C which is moderate thermal stress zone, and finally, 101 cases had average UTCI between 32–36.64°C which is strong heat stress. This result shows that paying attention to parameters affecting the outdoor environment can be very important and significantly increase the useability and thermal comfort of users of these spaces. Therefore, creating tools based on the framework proposed in this research can be very significant for designers and urban planners, especially in the early design phases.

In the next part of the research, by examining the results of the trained pix2pix model, it was proved that it is possible to use this method to predict comfort conditions in different designs. The model created in this research predicted the output maps of the test sets with an average of 96% accuracy. In addition, this model takes about 3 s to predict the UTCI index map. However, if the traditional simulation method is used alone, without taking into account the time required for modeling, analysis of outputs, and calculation of UTCI, it can take 10–40 min for similar. This high time cost makes simulation in the early design stages an unviable option. However, with the machine learning method in a space of a few minutes, dozens of design alternatives can be assessed.

However previous studies such as one done by Pezzuto et al. (2022) and Diz-mellado et al. (2021) have used machine learning models for OTC predictions, the present study is based on learning models with image-to-image translation. This approach has several advantages. The most important advantage is a more understandable output since the output of the UTCI map compared to the average PMV index as a single number shows different UTCI levels and it is more comprehensible for the user without familiarity with thermal comfort indexes than an abstract index number. Secondly, this model is easier to use. Input for this method is a single colour-coded image which makes it easier to use than a model with abstract features with the user should provide. Lastly, this model provides much more information to the user. This information includes the impact of various factors on comfort, the difference between the maximum and minimum UTCI in the design, etc., since the user can visually see how each parameter affected the thermal comfort in the designed area. Due to the difference between these two studies, it is not possible to compare the accuracy of the results of this study with these two studies. However, other studies using the pix2pix algorithm such as the research done by Jia (2021) and the research done by He et al. (2021) were able to train the pix2pix algorithm to predict daylighting maps with SSIM of around 0.9 which shows that the accuracy of this research by the mean SSIM of 0.96. Finally, due to the high accuracy and speed and the large amount of information that this method can provide users, it can be concluded that creating machine learning models such as the model presented in this research can be accurate, very fast, and simple to use.

However, this method is only in its early stages of development, and for it to be used more practically several steps should be taken, and some problems should be fixed. Firstly, this model can be expanded and improved with the introduction of more training data. This can have two effects where, firstly, the model accuracy would improve with bigger training datasets, and secondly, with more diverse training examples, the model's ability to predict output maps for more unpredictable inputs would improve.

Secondly, this method is restricted concerning inputs in two ways. Firstly, since images are being used as input, some numerical inputs such as meteorological data like air temperature and wind speed, are hard to be implemented in the model. Meteorological parameters being constant in this model mean that the current model can only evaluate the conditions for a design or an urban environment only in one geographical location and at one time. Secondly, although different parameters such as different building heights and materials could be shown with different colours, the usable colours are limited too since using similar colours might increase the model's error. Therefore, by implementing new strategies it might be possible to train machine learning models that can predict thermal comfort for different urban setups and different boundary conditions. With this being said, still evaluating designs in the critical states such as done in this research could be very insightful for urban designers and planners.

Finally, in the process of training the pix2pix algorithm, the quality of images is lowered to lower the pixel count and therefore to shorten the training time of the algorithm. This may have resulted in low-quality outputs; however, it should be mentioned that output images could be conceivably upscaled to higher quality through image processing. It is also worth mentioning that output images with their current quality are still usable and completely comprehendible and image upscaling and enhancing is out of this research's scope. Furthermore, although the geometry in the built urban environment is not likely to be changed other parameters regarding it can change such as vegetation and façade materials. Therefore, the results of this research apply to studying the effects of renovations or other changes in the urban context.

5. Conclusion

This research intended to create a novel framework for predicting OTC using machine learning and assess their ability and useability. In this research, the pix2pix algorithm was used and the results were very remarkable. This shows that machine learning can be used in this field as a very powerful tool. Until the writing of this manuscript, very few researchers have attempted to use machine learning for evaluating different design scenarios' thermal comfort performance. However, through this research, it has been shown that machine learning could be used for predicting thermal maps with high accuracy (average SSIM index of 0.96 on the test dataset) compared to the original ENVI-met 4.4.6 outputs in much higher speeds (1–2 s of simulation time compared to 15–35 min of ENVI-met 4.4.6). Since this research was concerned mainly with creating a framework for using machine learning in this field, many different parameters were not studied in this research. So future works can expand studied parameters with bigger datasets and expand on this research's current dataset.

One of the shortcomings of the pix2pix algorithm is translating climatic context to a visual input for the algorithm. Because of this restriction, this research only explored one climatic context at a specific time in the day. In future works, this aspect can be tackled by creating other innovative solutions for this problem. Another way of facing this problem is training other separate models for different climatic contexts which future research can also focus on.

Lastly, with numerous different approaches to machine learning problems and numerous machine learning algorithms, the use of other algorithms and processes different than the one suggested in this research could be explored.

6. Abbreviations

Greek symbols

$\mu_{x\ or\ y}$	Average over X or Y axis
σ_{xy}	Covariance of X and Y
σ_x^2 or σ_y^2	Variance over X or Y

Acronyms

ANN	Artificial neural network
GAN	Generative adversarial network
cGAN	convolutional GAN
SVM	Support Vector Machine
SSIM	Structural similarity index
MAE	Mean average error
OTC	Outdoor thermal comfort
PET	Psychological equivalent temperature
UTCI	Universal Thermal Climate Index
SET*	new Standard Effective Temperature
PMV	Predicted mean vote
MRT	Mean Radiant Temperature
SVF	Sky view factor
LAI	Leaf area index
sDA	Spatial daylight autonomy
UDI	Useful daylight illuminances
C	Celsius

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