

Article

Machine Learning for Pedestrian-Level Wind Comfort Analysis

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Abstract: (1) Background: Artificial intelligence (AI) and machine learning (ML) techniques are being more widely employed in the field of wind engineering. Nevertheless, there is a scarcity of research on the comfort of pedestrians in terms of wind conditions with respect to building design, particularly in historic sites. (2) Objectives: This research aims to evaluate ML- and computational fluid dynamics (CFD)-based pedestrian wind comfort (PWC) analysis outputs using a novel method that relies on the sophisticated handling of image data. The goal is to propose a novel assessment method to enhance the efficiency of AI models over different urban scenarios. (3) Methodology: The stages include the analysis of climate data, CFD analysis with OpenFOAM, ML analysis using Autodesk Forma, and comparisons of the CFD and ML results using a novel image similarity assessment method based on the SSIM, MSE, and PSNR metrics. (4) Conclusions: This study effectively demonstrates the considerable potential of utilizing ML as a supplementary tool for evaluating PWC. It maintains a high degree of accuracy and precision, allowing for rapid and effective assessments. The methodology for precise comparison of two visual outputs in the absence of numerical data allows for more objective and pertinent comparisons, as it eliminates any potential distortions. (5) Recommendations: Additional research can explore the integration of ML models with climate data and different case studies, thus expanding the scope of wind comfort studies.

Keywords: pedestrian wind comfort; computational fluid dynamics; machine learning; cultural heritage



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1. Introduction

Wind, a natural element in architectural design, can improve air conditioning [1], indoor comfort [2–4], and health [5], offering cost-effective and energy-efficient solutions. Light winds are advantageous in terms of ventilation and improved outdoor wind comfort, whereas strong winds necessitate detailed planning to prevent discomfort caused by high wind velocities [6]. The design of urban spaces exerts an impact on wind speed, which has a significant impact on the comfort of pedestrians, as the air currents generated by buildings can obstruct movement and lead to discomfort. The shape, height, and layout of buildings are crucial considerations in this regard [7–14]. The vertical dimension of a rectangular building can influence the velocity of wind in its close proximity, as higher structures can redirect and impede the movement of air [1–3]. Therefore, the consideration of wind in the design stage plays a vital role in ensuring the livability of architecture [10]. There is a growing emphasis on measuring wind comfort in urban environments, necessitating improved collaboration among urban planners, architects, and wind engineers, as well as enhanced collective research on urban space planning [3].

Pedestrian comfort in low-wind conditions induced by buildings and vortices is evaluated through wind analysis, for which fluid-mechanics-based approaches are typically employed [15]. For the evaluation of pedestrian wind comfort, the required dimensions are (i) comfort criteria derived from pedestrian wind comfort perceptions and local wind velocities; (ii) typical wind conditions derived from local meteorological data; and (iii) the

local aerodynamics of the building and its environment [2,16,17]. Commonly used comfort criteria for evaluating pedestrian wind comfort include the Lawson, Davenport, and NEN8100 Criteria. Lawson restricts wind speed for certain activities, whereas Davenport examines comfort based on established parameters and NEN8100 classifies comfort levels according to the probability of exceeding 5 m/s wind speed for each activity [17]. There are also modified versions of these comfort criteria; for example, London's City guideline employs Lawson as a basis and recommends measuring wind speed at a height of 1.5 m above the ground and establishes acceptable wind speeds for engaging in outdoor activities [2].

In terms of wind prediction for providing pedestrian comfort, the utilization of simulations for assessment of wind comfort and modeling in the design process enhances efficiency in terms of labor and time. Wind tunnel testing [1,14,18], field observations [14,18], and computational fluid dynamics (CFD) simulations [18,19] are commonly employed techniques in building layout and urban wind studies.

Despite being useful for design optimization, the installation of wind tunnels is expensive and time-consuming [20,21]. Therefore, numerical models and simulations such as CFD for wind patterns or CONTAM for interior air quality are frequently employed due to their thorough, precise, and cost-effective nature, particularly in the context of buildings [5,22]. However, certain guidelines should be followed to ensure the accuracy and precision of these results. In this context, CFD guidelines have been published by AIJ (Japan), COST (Germany), and City of London (CoL), which emphasize architectural design more than previous guidelines with more emphasis on wind engineering and industrial aspects [2,23,24]. AIJ incorporates principles of wind engineering and CFD across several test scenarios, whereas the COST guidelines establish a structure for assessing the sensitivity levels of numerical simulations. The CoL regulations utilize intricate 3D CFD models to accurately represent both present and future buildings, together with the surrounding pedestrian areas [2]. Reynolds-averaged Navier–Stokes (RANS) equations are employed to model fluid flows in these guidelines. Among these guidelines, the AIJ guidelines are considered the most efficient for evaluating wind conditions for pedestrians in the vicinity of buildings [23–25].

Regarding pedestrian wind comfort, CFD simulations have been employed in numerous studies to estimate the wind environment around buildings [26–32]. A considerable number of research studies [3,33,34] have improved the accuracy of these estimations through the use of CFD simulations in combination with a comfort metric. Despite its widespread use, CFD simulation is constrained by its significant computational burden due to the requirement of expensive computational resources, hardware equipment, engineering knowledge, and domain experience [1,20,31,35,36]. Considering these limitations of conventional methods, there has been an increasing trend regarding the use of AI-based techniques, which offer comparable accuracy and speed to conventional approaches. In addition, machine learning and artificial intelligence (ML/AI)-based methods are extremely efficient and have been widely utilized in multiple disciplines to improve various aspects of daily life, for example, optimizing signal transmission in wireless networks through enhancing the efficiency of text categorization techniques or directing signals based on user categorization. Additionally, such approaches allow for the forecasting of energy efficiency and energy consumption, specifically in relation to wind energy [37–42]. They are economical to implement and do not require any specialized expertise. The integration of AI and ML approaches can accelerate the decision making process and optimization in the design context [37,41]. Nevertheless, their efficacy is constrained by the accessibility of varied training data and the need to adjust to specific circumstances. There is an obvious scarcity of research on increasing pedestrian wind comfort in the field of building design, particularly in historic areas, despite the expanding use of AI and ML in the field of wind engineering.

The problem considered in this study is evaluating the efficacy of ML simulations in forecasting pedestrian wind comfort levels in a historical urban setting. The case study area in question is notable for its status as a UNESCO World Heritage site. To assess

the accuracy of the used ML approach, the results will be compared with those obtained through CFD. However, the output of the ML model is an image file without numerical data in the majority of cases. Therefore, a new approach is required in order to compare image files and assess the accuracy of wind comfort simulations. Employing such a novel method, the objective of this study is to conduct pedestrian comfort research by utilizing an ML approach, incorporating an urban scenario for comparison purposes. The emerging research questions can be summarized as follows: (i) How accurate are ML-based analyses when compared to CFD studies in predicting the wind comfort of pedestrians, and what are their limitations? (ii) What is the potential contribution of ML to the advancement of comfortable urban environments, specifically during the initial design stages? (iii) How can ML models be enhanced to refine the comparison of visual outputs and generate numerical results for wind comfort assessments? On the basis of these questions, the expected results can be outlined as follows: (i) the comparison methodology is expected to accurately measure similarity between the ML and CFD outputs; and (ii) overcoming the problem related to the limited ability to compare image-based outputs will open a new avenue for the widespread usage of ML and contribute to the sustainable development of urban areas, as well as creating a basis for further investigation and validation of ML-based wind analyses relying on image-based outputs.

In accordance with the subject matter, Section 2 presents an extensive examination of the applications of ML and CFD in the domains of urban planning, building design, and architecture, with a specific emphasis on wind analysis and the well-being of pedestrians. Section 3 encompasses the methodologies and materials utilized to evaluate the wind comfort of pedestrians within the designated historical region, while Section 4 elaborates the outcomes of the pedestrian wind comfort study, incorporating the results of the ML-based analysis with a comparison between CFD and ML analyses employing the proposed approach. Section 5 presents the key findings, namely, the correlation between ML predictions and CFD simulations using a novel method for comparing visual results with a specific focus on historical urban sites. This section also explores additional improvements to ML models that could be explored in future research to expand their usefulness in improving urban comfort and sustainability through the use of advanced ML techniques for environmental analysis.

2. Machine Learning for Wind Estimation in Built Environment

In recent years, there has been a considerable amount of research in the scientific community that has specifically concentrated on the utilization of ML tools with respect to built environments as well as environmental policies. These methods encompass the generation of design intent data, the integration of ML/AI, artificial neural networks (ANN) and deep learning in architectural design, and sustainable urban management in terms of energy efficiency, energy consumption, and infrastructure connectivity, as well as the utilization of ML as a tool at the intersection of art and architecture [37,41,43]. Moreover, the analysis of 2D and 3D data in generative design and the application of AI and ML in sustainable living spaces, urban policies and landscape design [41,43,44], and architectural plan generation [45], including the integration of ML into architectural education [14,46–52] and conservation of architectural heritage [53], are also important fields of research. In addition, ML methods have been utilized to forecast carbon emissions during the design stage, as well as to generate design choices for building design with regard to comfort and performance [49,54,55].

ML approaches are gaining popularity over CFD due to their efficient and extensive implementation, and as they do not require comprehensive prior knowledge. The most recent ML models for assessing pedestrian-level wind conditions are provided by Autodesk Forma, Orbital Stack, and InFraReD [56]. Autodesk Forma is aimed at providing guidance in the early design process. The analysis can be run instantly and provides wind simulation results reflecting how the wind conditions change based on the design. Orbital Stack, a development by Neural Concept, leverages a comprehensive dataset to train its

algorithms. This emphasis on data-driven accuracy aims to refine the predictive capabilities of simulations during the early design phases [57]. The Intelligent Framework for Resilient Design (InFraReD), initiated by the City Intelligence Lab at the Austrian Institute of Technology, integrates ML with augmented reality (AR) to predict and visualize wind conditions around buildings [58]. This approach allows for an immersive design experience, facilitating wind-related decision-making through a blend of predictive analytics and interactive visualization. Among these tools, Autodesk Forma is uniquely accessible for research applications, making it an ideal candidate for this study. Its availability and comprehensive functionality for early design guidance offer significant advantages for investigating wind conditions and their implications for pedestrian comfort.

The machine learning process generally comprises five essential steps: data collection, data preparation, training, evaluation, and parameter tweaking. After being trained with data acquired from analytical solutions, numerical simulations, experimental testing, or full-scale measurements, the learning model gains the ability to forecast future or unknown events. The algorithms utilized in wind engineering for AI and ML techniques can be classified into four categories: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Supervised learning uses data that have been labeled, unsupervised learning uses data that have not been labeled, and semi-supervised learning uses both. Reinforcement learning learns knowledge through trial and error, without relying on prior data. Hence, the dependability of a machine learning model is constrained by the available data [59]. Researchers have utilized ML approaches to predict thermal comfort and ventilation, emphasizing wind speed/velocity, wind impact, wind direction, flows, and overall comfort in the built environment [1,11,16,60–63]. Scientific research has placed significant emphasis on the application of ML techniques in the domains of energy conversion and management, building management, structures, and urban areas, particularly when related to physics. In recent years, the utilization of ML methods for assessing urban air quality, microclimate prediction for wind farms, wind load estimation, and wind pressure prediction has been growing [33,64–69], and research focused on testing various approaches and algorithms has gained momentum in recent years (Table 1).

Table 1. Research on buildings, structures, and urban spaces related to wind effects using ML [11,12,14,19,20,34,35,63,65,66,70–90].

Area of Focus	Author	Aim/Focus	Methodology	Findings
Wind speed	[70]	To enhance the precision of wind speed forecasting	NNN	NNN model is effective for wind-speed forecasting.
	[63]	Wind speed prediction	NAR, NARX	NARX model showed superior performance with fewer data in order to obtain a more accurate prediction compared to NAR, which was statistically significant.
	[71]	Outdoor wind speed simulations	U-Net	The U-Net model is a baseline for fast, data-driven wind flow prediction. Innovative or physics-informed model architectures can be provided for better results.
	[65]	Combining spatial and frequency characteristics to enhance prediction of pedestrian wind flow	GAN based SFGAN	SFGAN improves prediction accuracy by analyzing the spatial and frequency aspects of wind, enabling the evaluation of wind comfort with various building morphologies.

Table 1. Cont.

Area of Focus	Author	Aim/Focus	Methodology	Findings
Wind speed	[72]	To assess the impact of buildings, streets, and other urban features on wind flow	Different methods including k-Nearest Neighbors (kNN) regression	kNN regression has given the highest accuracy. ML-based models are capable of predicting wind flow.
	[14]	To propose a NN structure for the rapid reconstruction of urban wind fields using sparse sensor data	DL model	The DL model is effective in collecting wind data with sparse sensors.
	[73]	To evaluate ML workflows (MLWs) for predicting wind comfort levels	U-Net	ML models are efficient for prediction, but improvements are needed for pedestrian safety.
Wind power	[74]	Analyzed the capacity of ML for wind power prediction	ML algorithms	Utilization of ML algorithms before establishment of wind plants in an unknown location.
	[42]	Investigated the potential of AI in enhancing urban wind energy through positioning of turbines	ANN	AI applications are successful in determining the most advantageous positions for turbines.
	[75]	Investigated the efficacy of ML for wind power prediction	CityFFD	Emphasized the efficacy of ML for wind power prediction and the impact of neighborhood characteristics on the potential of wind energy.
Overall comfort—wind comfort	[76]	Assessed the applicability of BRT models to forecast cold-air paths	BRT	Reliable training datasets and additional tests in different locations are required to improve the reliability of these models.
	[34]	Compared CFD and InFraRed in an effort to optimize solar radiation exposure and outdoor wind comfort during the urban design process	InFraRed	InFraRed is efficient in the design process for wind-related decisions.
	[35]	Utilized InFraRed methods for wind prediction in the design phase	InFraRed	Integrating InFraRed methods in the early phases of design can improve outdoor wind comfort.
	[11]	Examined the relationship between environmental variables and the level of thermal and wind comfort experienced in outdoor areas	ML model	ML can serve as a reliable supplement to CFD simulation in the field of urban studies.
Wind pressure	[77]	Developed a predictive model using ANNs to pressure coefficients on the gable roofs of low-rise buildings	ANN	The potential of using ANNs to expand aerodynamic databases for a wider variety of building geometries and conditions, thereby increasing the practical feasibility of designing buildings, is highlighted.
	[65]	Prediction of wind forced coefficients of rectangular buildings	ANN, BPNN, RBFNN, GRNN	RBFNN stands out as the optimal choice for predicting wind coefficients.
	[78]	Prediction of wind-induced pressures on high-rise buildings	BPNN, POD (POD-BPNN)	POD-BPNN approach can successfully and efficiently predict the time-series of pressure data on all surfaces of a high-rise building.
	[79]	Developed a method to predict roof pressures on low-rise structures caused by freestream turbulence	ANN	The ANN model achieved high accuracy in predicting peak pressure coefficients and could effectively interpolate wind pressures on low-rise buildings.

Table 1. Cont.

Area of Focus	Author	Aim/Focus	Methodology	Findings
Wind pressure	[80]	Developed and validated a computational modeling approach using ANN to predict the mean wind pressure coefficient on the surfaces of buildings with flat, gable, and hip roofs.	ANN	ANN demonstrated higher accuracy than the traditional parametric equations in estimating pressure coefficients across different types of roofs and building configurations.
	[81]	Prediction of wind pressure coefficients on tall buildings	Decision Tree, Random Forest, XGBoost, Generative Adversarial Networks (GANs)	The GAN model demonstrated the best performance, which was capable of accurately predicting wind pressure coefficients under unseen interference conditions.
	[82]	Introduced a deep neural network (DNN) approach for predicting wind pressure coefficients on low-rise, gable roof buildings	DNN	DNN model demonstrated high accuracy in predicting mean and peak wind pressure coefficients.
	[83]	Evaluated the feasibility and effectiveness of different ML algorithms for predicting wind pressures on high-rise buildings	ML algorithms (ridge regression, decision tree, random forest, gradient boosting regression tree)	The gradient boosting regression tree model showed the best performance as an efficient and cost-effective method for predicting wind pressures on high-rise buildings.
	[84]	Addressed the challenge of interpreting ML models predicting wind pressure coefficients on low-rise gable-roofed buildings	Decision Tree, XGBoost, Extra-tree, LightGBM	Tree-based regression models are efficient and accurate in predicting wind pressure coefficients for low-rise gable-roofed buildings.
Wind-induced interference	[85]	Investigated wind-induced interference effects on buildings, focusing on how adjacent buildings modify wind loads	ANN	This study laid the groundwork for using neural networks. An ANN method is developed to assess wind-induced interference effects on buildings more systematically, accounting for the large number of influencing variables and the limited data availability.
	[86]	Quantified the effects of shielding and interference between pairs of buildings in various geometric configurations and boundary-layer wind flows using ANN	ANN	Quantified the shielding and interference effects between buildings in a variety of configurations. Predicted the wind-induced effects in urban environments with ANN.
	[87]	Evaluated the interference effects among adjacent buildings under wind action	ANN, RBF neural network (RBFNN)	The results demonstrated the efficacy of the RBFNN in modeling and predicting complex wind interference among tall buildings in urban environments.
Wind load and microclimate around buildings	[88]	Employed neural networks to predict wind load distribution on air-supported structures, utilizing experimental data for training	ANN	Highlighted the potential of neural networks in structural engineering applications, particularly in predicting wind loads on complex structures with limited direct experimental data.
	[66]	Prediction of wind loads on buildings, specifically focusing on a large flat roof, using fuzzy neural networks (FNN)	FNN	FNN approach could generalize functional relationships of wind loads varying with incident wind directions and spatial locations on the roof. It could reduce the complexity and scope of pressure measurement programs.

Table 1. Cont.

Area of Focus	Author	Aim/Focus	Methodology	Findings
	[89]	Prediction of the microclimate around buildings	ANN, GIS, CFD	Combined methodology has potential to predict microclimates for urban planning and building performance studies.
	[90]	Optimized the spatial configuration of urban systems through integrating multiple simulation engines including DL estimations of microclimate with graph-based mobility and accessibility models	DL	Through reducing computing time and incorporating many essential performance metrics, the advantages of using DL-based estimations in the design process have been demonstrated.

Regarding the estimation of wind speed using ML, Ref. [71] trained a U-Net model using numerous CFD simulation output as the dataset. While generally effective, this method encountered difficulties when applied to high-density urban areas, resulting in disturbances at the layout boundaries and reduced precision of wind flow patterns. The study emphasized the straightforwardness and efficiency of U-Net, while indicating that employing more sophisticated or physics-based models may enhance outcomes. This is one of the first studies to utilize artificial intelligence for rapid surrogate modeling in urban layout analysis [71]. Ref. [63] addressed wind speed prediction through the utilization of two neural network architectures: the non-linear autoregressive neural network (NAR) and the NAR with exogenous inputs (NARX). The obtained results demonstrated the efficacy of these models in the domain of time-series forecasting. Notably, NARX surpassed NAR in terms of accuracy and data reduction, signifying a statistically significant progression in wind speed prediction [63]. Ref. [70] devised enhanced non-linear neural network models to enhance the precision of wind speed forecasting. Through the process of fine-tuning the parameters of the neural network, their models achieved a notable improvement in accuracy and reduction in error rates compared to older methods. The results of this study emphasize the efficacy of advanced optimization strategies in improving the accuracy of wind speed predictions [70].

The use of ML also expedites forecasts in the domain of wind power and wind energy. Refs. [74,75] emphasized the efficacy of ML in forecasting wind power. Considering the potential of ML to predict wind power in novel regions utilizing daily wind speed data, Demolli et al. demonstrated how ML can predict wind power in various locations. By combining ML with CFD and City Fast Fluid Dynamics (CityFFD) simulations, Mortezaazadeh et al. analyzed the potential of urban wind power, specifically regarding roof-mounted turbines. The results of their study verified the precision of ML in urban environments and emphasized the impact of neighborhood attributes, rather than the height of buildings, on the wind energy potential. They recommended that future wind energy research consider the urban morphology [74,75]. Ref. [42] conducted a comprehensive investigation on the potential of AI in enhancing urban wind energy by means of AI applications, database compilation, wind tunnel experiments, and CFD validations. The researchers examined the impact of building morphology on the positioning of turbines and wind velocities at ground level. An analysis was conducted to compare expert systems and ANN outputs, which revealed that the ANNs outperformed the former, attaining an accuracy of up to 99%. This study emphasized the capacity of AI approaches to determine the most advantageous positions for turbines, thereby promoting sustainable urban development and enhancing the efficiency of wind energy [42].

One domain of study in which ML techniques has been applied is the prediction of wind flow as it relates to pedestrian comfort. Ref. [65] created the Spatial-Frequency Generative Adversarial Network (SFGAN) to precisely forecast the movement of wind around pedestrians, which was achieved by specifically addressing the spatial frequency

bias that exists in conventional GANs. SFGAN improves the prediction accuracy through incorporating a spatial frequency loss and analyzing the spatial and frequency aspects of wind. This enables architects to evaluate wind comfort more effectively with respect to various building morphologies [65]. Ref. [1] proposed a new conceptual framework called Wind-Sensitive Urban Design (WiSUD), which aims to integrate wind factors into urban planning and design in order to support cities in achieving carbon neutrality. A PRISMA-based systematic review was carried out to establish a wind-sensitive urban design framework, with a specific focus on the advantages of urban wind in terms of ventilation and energy generation. Their research emphasized the necessity of improved turbine and wind evaluation technology, as well as a more comprehensive understanding of local urban environments [1].

Ref. [72] employed machine learning methods—specifically neural networks and regression trees—to examine the impact of urban elements such as buildings and streets on wind flow. Their research, which utilized an ML algorithm trained with gathered data, emphasized that flow patterns are impacted by local attributes such as surrounding building features and cell height. They discovered that the ML approach was less complicated, when compared to RANS simulations. However, their ML model had several limitations, such as its emphasis on flat surfaces and its ability to only consider a single wind direction. The authors recommended that future research should encompass different topographies and wind directions [72]. In another study, Ref. [14] described a deep learning model that utilizes a Graph Convolutional Network (GCN) and an auto-encoder architecture to reconstruct urban wind fields from sparse sensor data. Through integrating physical information into the model and enhancing sensor–environment correlations, the prediction errors of the model were decreased. While this method is useful for basic wind field data analysis, it has certain limitations including the lack of real-world data verification and the possibility of errors due to insufficient data reflecting rapidly changing conditions [14].

Other areas where prediction is conducted with ML techniques involve wind comfort and wind condition. RWDI conducted a study utilizing ML—specifically the Orbital Stack CFD method—to forecast wind conditions in pedestrian zones of a residential neighborhood. This method succeeded at urban wind modeling during the early design phase, complex flow analysis, and the identification of problematic wind conditions. The study provided a comprehensive investigation of pedestrian wind comfort, proposing the use of wind tunnels for evaluating solutions at the design stage [2]. In their study, Ref. [73] evaluated two ML workflows (MLWs) that utilize U-Net regression and classification models to forecast wind comfort. The researchers analyzed 213 simulations and 8 wind directions, in accordance with the Lawson LDDC criterion. The models were found to be efficient, decreasing the computational time from 26 h to a matter of seconds, and the training data were expanded through the use of scenario-based methods. Although they were successful in making predictions, they are limited to certain situations and require enhancements to ensure pedestrian safety; furthermore, they require additional simulation and re-training in order to be widely applicable [73].

Ref. [11] examined the relationship between environmental variables and the level of thermal and wind comfort experienced in outdoor areas near buildings. The ML technique relies on learning algorithms to analyze patterns, structures, and correlations between labeled features and targets in the Python Environment. The ML results were less accurate than those generated through CFD simulations; nevertheless, the research indicated that ML could serve as a reliable supplement to CFD simulation in the field of urban studies [11]. Ref. [76] employed Boosted Regression Tree (BRT) modeling to forecast cold-air paths and assessed the applicability of these models to different urban regions. They utilized a range of predictor variables, encompassing thermal, aerodynamic, and topographic features. Their findings emphasized the necessity of training datasets and additional tests in different locations to improve the reliability of these methods for urban planning [76]. Refs. [19,35] conducted a comparison between CFD and InFraRed in an effort to optimize solar radiation exposure and outdoor wind comfort during the urban design process. The process included

multiple stages, using digital design software and plug-ins such as Grasshopper for Rhino, ML-based InFraRed for wind prediction, and CFD tools as Procedural Compute and Butterfly for wind analysis. The analysis examined how fluid design affects wind flow and shading when using InFraRed prediction, which was confirmed through validation with CFD. The reliability of InFraRed facilitates its integration into early design phases for wind-related decision making. In terms of the limitations, it was emphasized that although the basic operation of InFraRed and Ladybug in Grasshopper is simple, CFD analyses with Butterfly necessitate expertise; furthermore, the inability of InFraRed to consider terrain morphology and its training on basic building extrusions may decrease the final accuracy. In another study, InFraRed methods were used for wind prediction in the design phase. The method was validated using Grasshopper CFD plug-ins (e.g., Butterfly for Grasshopper) and cloud-based Procedural Compute. The study showed that the integration of InFraRed methods in the early phases of design can improve outdoor wind comfort. The limits were stated as a constrained budget for the architectural project and a lack of expertise in the terrain morphology of InFraRed [19,35]. Ref. [90] aimed to integrate deep learning technology (for real-time prediction of microclimate factors such as thermal comfort and wind speed) with graph-based models of mobility and accessibility (to enhance the spatial layout of urban systems). The results indicated that the reduction in computing time makes it easier to include DL-based estimations in the design process. Integrating several key performance measures resulted in the development of more significant goals, such as combining thermal comfort and pedestrian flow metrics [90]. Nevertheless, the selection process still demonstrates a limited and conventional set of criteria, indicating the necessity for a broader approach to evaluate urban morphologies.

The literature review revealed that studies on wind analysis in the design phase usually conclude that ML and AI methods speed up the design process and provide comparable accuracy to simulations. Consequently, they are effective in the early design phase of the building/urban design process, and they are inexpensive to implement and do not require specialized knowledge. However, there is a need to expand the training data, encompass terrains with diverse characteristics, and conduct further experimental tests [11,71,76]. The models are constrained by their reliance on case studies, making them difficult to adapt to different circumstances and inaccurate in areas with inadequate training data.

In addition to the aforementioned studies, research examining the comfort of pedestrians in historic areas using ML was not encountered in the review. It is evident that additional testing and validation are required in this area. In this context, the research problem considered in this study the comparison of ML and CFD simulation models for an urban scenario in order to assess the effectiveness of ML simulations in predicting pedestrian wind comfort levels and provide recommendations for a more comfortable outdoor environment.

3. Materials and Methods

In this section, the details of the materials and methodology used in the study are given as distinct sections. The first provides the descriptions of and selection criteria for the subject material, while the second covers the methodology and process that was followed to evaluate the material.

3.1. Materials

The case study site is the Khans Region in Bursa, Turkey. The district was accepted as a UNESCO World Heritage Site in 2014. The Khans Region is a cultural and touristic zone located at an elevation of 228 m above sea level, characterized by mostly low- and mid-rise structures and a semi-open layout that is exposed to wind influences. The region underwent development in alignment with the urbanization framework of the Ottoman Empire. Its formation commenced under the rule of Orhan Gazi and persisted under the reigns of Yıldırım Bayezid and Çelebi Mehmet, who prioritized the organization of trade routes and city planning. The district began to develop in the 14th century under the Ottoman

Empire and had evolved into an important center for international trade by the late 16th century, when major commercial routes crossed through Bursa [91]. Different mosques, inns, bazaars, Bedesten, madrasahs, and temples were constructed in the Inns District during the reign of Yıldırım Bayezid, in addition to the Ulu Mosque. Ottoman inns are characterized by a two-story structure featuring chambers that face the central courtyard, which are square or nearly square in shape; this architectural style led to the designation of the area as a UNESCO World Heritage Site. The historic bazaar and inns district, situated along the Silk Road route and constituting an integral part of Bursa—the inaugural Ottoman capital—continues to uphold its conventional commercial character. With restorations, certain inns have endured to the present day in a functional state and continue to be utilized most prominently for social, food and beverage, and commercial purposes.

In 2011, the Bursa Metropolitan Municipality announced an architectural proposal competition to improve the central square of the region, which was completed in 2012. A part of the approved project was built in 2016, and the area functions dynamically [92]. In 2020, the Bursa Metropolitan Municipality initiated a new urban design project, covering a larger scale of the Khans Region and the surrounding area. The winning project, which began to be implemented in 2021, is close to completion at present. The project and implementation have enhanced pedestrian circulation, making it more pleasant and effective. The Khans Region and the surrounding area, which are parts of the UNESCO Heritage Site, are attractive to urban dwellers as well as local and international tourists. For this reason, ensuring pedestrian wind comfort is crucial for facilitating the comfortable use of an area that experiences dense and significant daily and touristic pedestrian circulation.

There are many historical buildings located in the case study area (see Figures 1 and 2). Most of these buildings are nearly the same height (e.g., 10 m) and have two floors from the ground level. The site plan of the case study area and an aerial photo are provided in Figure 1.

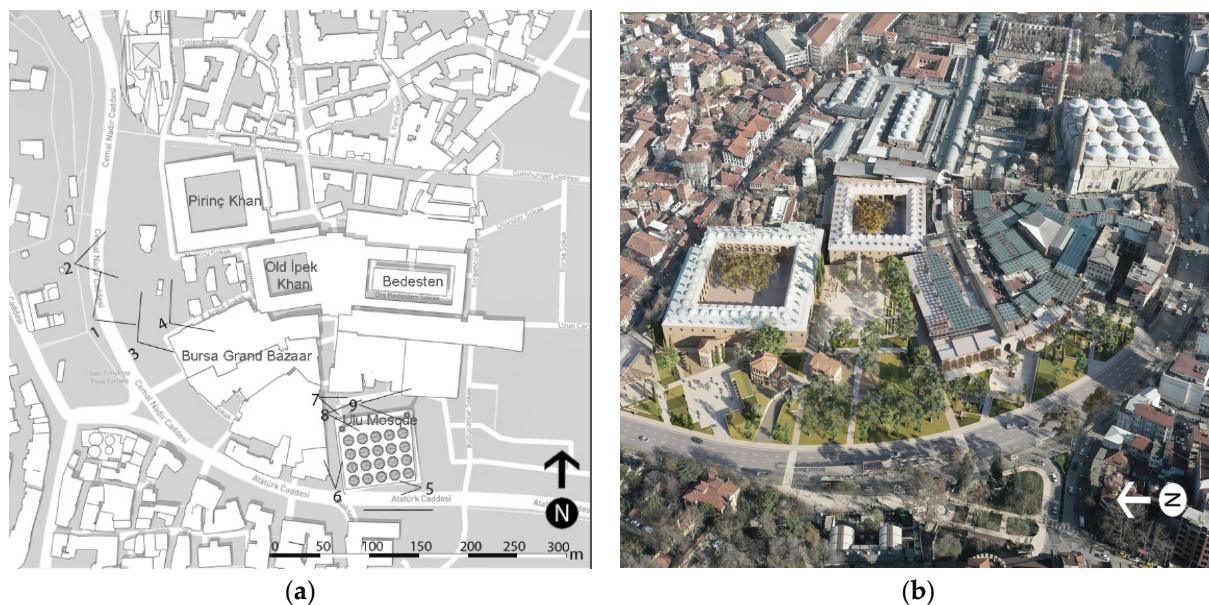


Figure 1. Site plan of the case study area (a); aerial photography of the case study area (b).

3.2. Methods

The four stages of the methodology are as follows: (i) analysis of climate data using meteorological data and the wind rose diagram; (ii) CFD analysis using RANS equations solved with the OpenFOAM v2312 software; (iii) ML analysis using Autodesk Forma's ML-based analysis tool; and (iv) comparisons of CFD and ML methods using a novel image-based comparison method based on SSIM, MSE, and PSNR metrics in order to achieve an objective and relevant comparison.



Figure 2. Images of the case study area.

Wind comfort assessment generally starts with climate data analysis. Therefore, a thorough understanding of the local climate based on a detailed analysis of long-term (at least 30 years) meteorological data is required [6]. Meteorological stations are generally located in open areas with an aerodynamic roughness length of $y_0 = 0.003$ m. At such stations, wind speed is measured at 10 m height, and mean wind speed values are observed on an hourly basis. A windrose of hourly mean wind speed for the location based on 30-year meteorological data (right) and the meteorological station locations (left) is shown in Figure 3 (the wind rose diagram was created using a Python script authored by the researchers). These meteorological data were transferred to the case study location and used as the inlet boundary condition in the CFD simulation to obtain wind-speed velocities at the pedestrian level, which is generally assumed to be 1.75 m.

3.2.1. Method for Computational Fluid Dynamics Analysis

The turbulent flow within urban or industrial environments is generally modeled using the Navier–Stokes equations [24]. Therefore, as an economical solution, steady-state 3D Reynolds-Averaged Navier–Stokes (RANS) equations were used. These equations were solved using the open-source CFD code OpenFOAM v2312, which is commonly part of engineering fluid dynamics software. In particular, to solve the governing equations for fluid flow, we used the solver simpleFoam from the OpenFOAM v2312 toolbox. The solver assumes that the flow is steady-state and incompressible, which is in line with the state of the art in the industry for wind analyses on a micro level. The realizable k-Epsilon turbulence model was chosen, as encouraged by relevant guidelines [2]. Turbulence modeling is a distinct research domain; however, this model is considered to provide reasonable outcomes for urban wind simulations. After running the simulation with the selected turbulence model, results were extracted if the solution converges, and the error estimate was minimal.

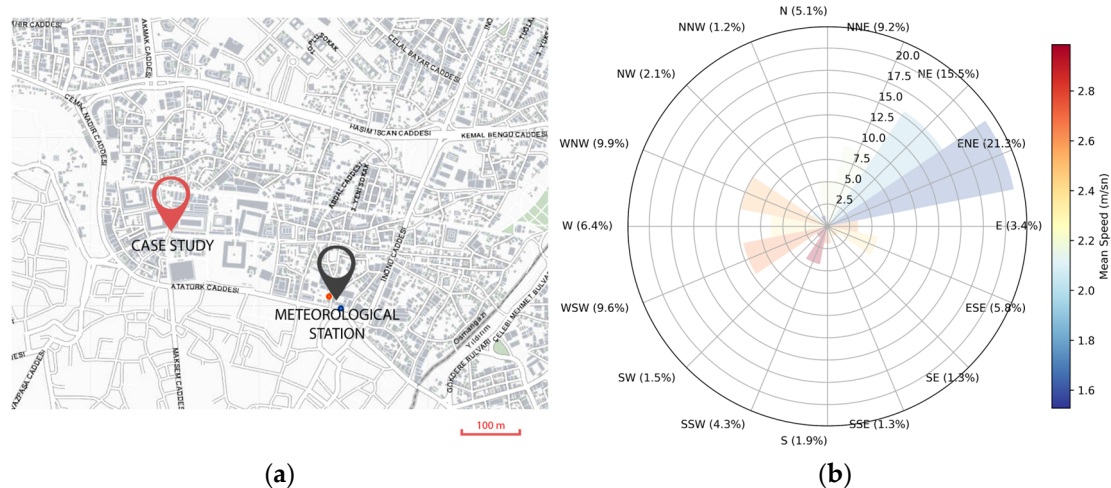


Figure 3. Meteorological station locations (a); wind rose of hourly mean wind speed for the location based on 30-year meteorological data obtained from the Turkish Meteorological Organization (b).

For the simulation, a large computational model was created and the computational domain (consisting of nearly 9.2 million cells) was divided into different zones with respect to aerodynamic roughness lengths. The near-field around the site of interest was modeled explicitly, while the far-field (including adjacent buildings) was modeled implicitly using an aerodynamic roughness length of $y_0 = 0.75$ m. The area with explicitly modeled buildings was 300 m in diameter. An upstream domain extension of $5H$ (where H is the height of the tallest building in the location of interest) and a downstream domain extension of $15H$ were left in the domain, as recommended by the guidelines. The area around the buildings was modeled in detail through using cells that were slightly smaller than those at the boundaries of the explicitly modeled region [2,24]. The volume occupied by the fluid was divided into a high-quality, high-resolution grid consisting only of discrete, hexahedral cells (the mesh). It was ensured that no cells around important areas were larger than 1 m. The pedestrian level height (1.75 m) was divided by at least 0.5 m sized cells in height, as has been previously recommended [24,93]. On the other hand, geometric elements with details more intricate than 1 m and which may impact the wind flow were also divided using high resolution meshes. However, it was also ensured that the corners of the building geometries remained sharp in the analysis. Moreover, a neutral atmospheric boundary layer was represented at the boundary of the computational domain. For this study, a logarithmic mean wind speed profile was used with a u_{10} (10 m from the ground) reference corresponding to mean wind speed for every wind direction. When environmental pressure was applied at the inlet, zero static pressure was applied at the outlet of the domain. Therefore, the flow passed through the entire domain and developed completely. In addition, the sides and top of the domain were modeled with zero normal velocity and zero normal gradients of all variables. Thus, there was no airflow friction at these domain boundaries.

Finally, the pedestrian comfort analysis combining the wind flow patterns with the frequency probabilities defined in the wind rose was conducted. For the wind comfort scale, a modified version of the Lawson LDDC wind comfort criteria, which has been widely used in the AEC industry, was chosen. This metric is also recognized as an effective method when it comes to assessing pedestrian wind comfort for urban environments in the City of London Wind Microclimate Guidelines [2]. The Lawson LDDC wind comfort criteria are a subset comprising 4 different categories; these categories use a probability of 5% as a fulfillment value. This criterion uses different threshold speeds and calculates the probability according to the CFD results, the meteorological and terrain information, and the wind rose data. Table 2 shows the upper limits of each activity category as a function of mean wind speed and the probability of occurrence for different wind comfort metrics. According to the Lawson LDDC scale, “sitting” is uncomfortable if the mean wind speed is

more than 2.5 m/s more than 5% of the time. On the other hand, for walking, humans can tolerate higher average winds, raising the acceptable average wind speed to 8 m/s for 5% of the time. Finally, a wind speed of 8 m/s and above is considered directly uncomfortable and, therefore, is not included in the table.

Table 2. Comparison of different wind comfort metrics.

	Sitting (Acceptable for Frequent Outdoor Sitting Use, e.g., Restaurant, Café)	Standing (Acceptable for Occasional Outdoor Seating, e.g., General Public Outdoor Spaces, Balconies, and Terraces Intended for Occasional Use)	Strolling (Acceptable for Entrances, Bus Stops, Covered Walkways, or Passageways Beneath Buildings)	Walking (Acceptable for External Pavements, Walkways)
Lawson	1.8 m/s, 2%	3.6 m/s, 2%	5.3 m/s, 2%	7.6 m/s, 2%
Lawson 2001	4.0 m/s, 5%	6.0 m/s, 5%	8.0 m/s, 5%	10 m/s, 5%
Lawson LDDC	2.5 m/s, 5%	4.0 m/s, 5%	6.0 m/s, 5%	8.0 m/s, 5%
Davenport	3.6 m/s, 1.5%	5.3 m/s, 1.5%	7.6 m/s, 1.5%	9.8 m/s, 1.5%
NEN 8100	5 m/s, 2.5%	5 m/s, 5.0%	5 m/s, 10%	5 m/s, 15%
CSTB	3.6 m/s, 5%	3.6 m/s, 5%	3.6 m/s, 10%	3.6 m/s, 20%

3.2.2. Method for Machine-Learning-Based Analysis

Within the scope of this study, the ML-based analysis tool of Autodesk Forma was used. This tool is aimed at providing guidance in the early design process. The analysis runs instantly and provides simulation results reflecting how the wind conditions change based on the design. A multivariate model based on an artificial neural network (ANN) is used for wind speed estimation. It combines multiple local measurements, such as wind direction and speed, over thousands of urban scenarios. The machine learning model was trained on simulation data assuming a mean wind speed of 3 m/s at 10 m height above the ground with an Atmospheric Boundary Layer (ABL) and considers 8 discrete wind directions for each site. Incorporating a training dataset consisting of real projects enables the model to learn the dynamics of wind flow across diverse sites characterized by varying building typologies and terrain features, with considerations for surrounding structures and proposed buildings during the training process. When adjusting the wind speed, the process involves linear interpolation of the existing prediction from 3 m/s to the selected speed, without necessitating the running of a new prediction.

The efficacy of the trained model is quantified by loss factor calculations. In machine learning, the term “loss factor” typically refers to a scalar value that quantifies the discrepancy between the predicted outputs of a model and the true values in the training data. The considered loss, calculated in meters per second (m/s), quantifies the disparity between the prediction and simulation for each pixel. The mean loss for a single site represents the average of these point-by-point comparisons across the entire prediction area. However, the black-box nature of commercial ML models presents a significant research challenge, as these models are usually not publicly shared due to confidentiality and commercial considerations. Therefore, researchers encounter constraints in numerically validating these models across various scenarios, especially concerning loss factor evaluations. This circumstance also serves as a crucial starting point for this study.

Finally, unlike CFD analysis—which simulates the air flow around buildings in detail—the ML model is predictive in nature. It estimates the ground wind level at each grid point based on the model’s understanding of architectural aerodynamics, rather than simulating the movement of the wind itself. In other words, the wind comfort results of the ML tool are based on predictions and are, therefore, more superficial than the simulation-based ones (results of the CFD analysis). This is why such approaches are mostly used as a tool in the early steps of architectural design. There are also other functional limitations: (i) although the results can be seen for a particular wind direction, there is no streamline view option to see the air flow patterns in detail; (ii) the results can only be seen at the pedestrian level while, in many cases, it is required to see the comfortable/uncomfortable

areas over the open/semi open spaces like balconies, terraces, and roofs; and, finally, (iii) the output provided by the ML model is only an image file—in other words, there is no numerical output.

3.2.3. Metrics to Compare CFD with ML

Following a manual review of the output quality, several evaluation metrics were used to quantify the success of the ML model. As indicated before, due to the limitations of the software (Autodesk Forma), numerical results are not achievable. Therefore, an image-based comparison method is the most viable option at this stage. In the evaluation of image processing algorithms, particularly in the domain of machine learning (ML), in which generated outputs are compared against target images, the precision in terms of similarity metrics is very important. This study employs a comprehensive approach to assess the similarity between colored images, incorporating the Structural Similarity Index (SSIM), Mean Squared Error (MSE), and Peak Signal-to-Noise Ratio (PSNR) as core metrics. These metrics were applied to original images, images with added noise, and images with adjusted contrast to objectively measure the model performance under varying conditions.

SSIM provides a measure of similarity between two images by considering changes in texture, luminance, and contrast, offering a more perceptually relevant assessment than pixel-based metrics [94]. MSE quantifies the average squared difference between the pixel intensities of the images, serving as a straightforward measure of error magnitude. PSNR, on the other hand, inversely relates the signal's maximum possible power to the power of corrupting noise, providing an indication of image quality at a glance [95].

This methodology's novelty lies in its handling of color and transparency within PNG images, using alpha channel information to exclude transparent pixels from the comparison, ensuring that only meaningful content contributes to the similarity assessment. This approach is especially pertinent in ML applications, where the generated images may contain regions of transparency or varying degrees of noise and contrast alterations.

The integration of SSIM, MSE, and PSNR into the evaluation framework aligns with recent trends in ML, where the fidelity of generated images with respect to their original counterparts is critical. For instance, Ref. [96] in their exploration of Generative Adversarial Networks (GANs) for image generation, employed similar metrics to quantify the realism and diversity of synthetic images [96]. Additionally, Ref. [97] used these metrics in the context of image-to-image translation tasks to evaluate the perceptual quality of transformed images against their original sources [97].

In brief, this methodology provides a detailed understanding of the ML model's performance in relation to the target image, which is the output of the CFD analysis, within the scope of this study. Through accurate comparison against established benchmarks, it contributes to the advancement of image processing/comparison techniques within the rapidly evolving field of machine learning.

4. Results

In this section, the outputs of the wind comfort studies are given as distinct sections. As indicated before, the pedestrian wind comfort (PWC) analysis was conducted to evaluate the impacts of wind interference due to the built environment on pedestrians. The wind comfort values, in the form of an exported site map that indicates which activities can be conducted and where, are the result of this analysis.

The following subsection presents and discusses the output of the CFD analysis, while the second subsection covers the output of the ML-based analysis. The last subsection provides the comparison of the results obtained from these two analyses.

4.1. Results of the CFD Analysis

In order to obtain accurate wind data, especially for future planning scenarios, wind tunnel experiments or computational fluid dynamics (CFD) analysis are essential. As wind tunnel studies are very complex, CFD approaches have been established as standard

in research practice with the aid of simulation programs. In urban environments, the microclimate and personal comfort are strongly influenced by the wind conditions. An output of the CFD analysis, illustrating the areas with a colored comfort scale, is shown in Figure 4.

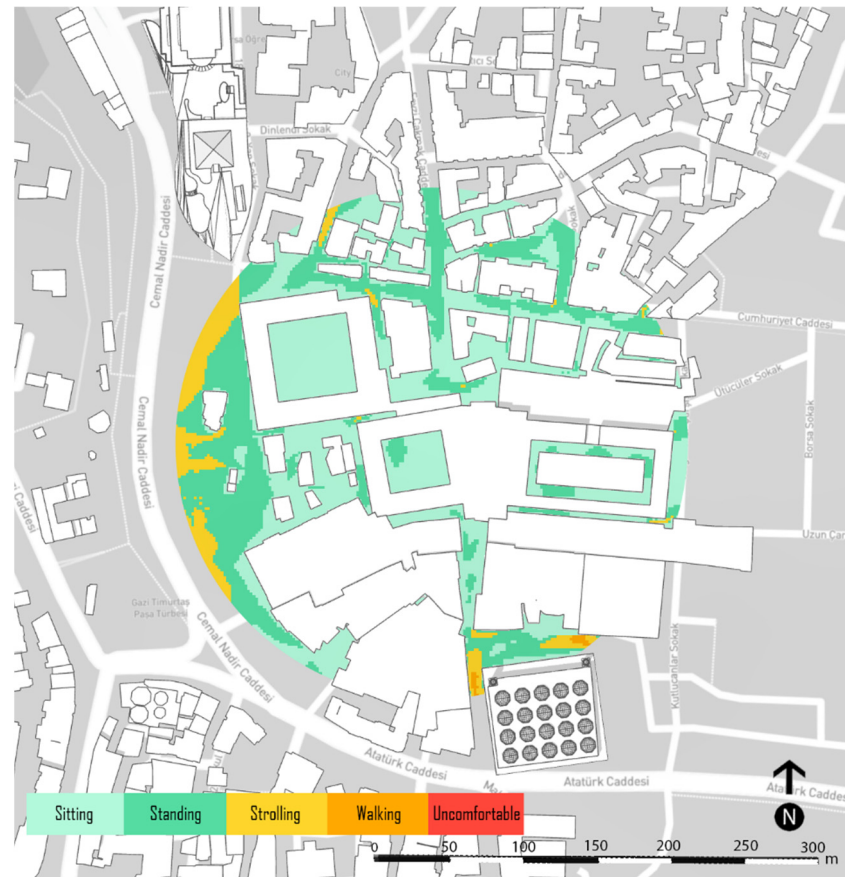


Figure 4. Pedestrian-level wind comfort analysis of the case study area using CFD software (OpenFOAM v2312).

Through the three-dimensional structure and disposition of building volumes within cities, it is possible to experience areas characterized by high wind speeds and turbulent wind gusts. Some of the effects that can occur include (i) the downdraught effect, (ii) the Venturi effect, and (iii) upwards deflection. These effects frequently cause high-velocity wind at ground level, which can cause severe disturbances. The wind flow theme can provide important clues as to which direction is causing pedestrian discomfort. Some locations in the area might be prone to wind from a specific direction, which is not always easy to interpret from the comfort analysis results alone. Therefore, in order to determine the particular effects related to different wind directions, direction-based analyses were also conducted.

While selecting the South wind direction and showing streamlines going through the point of interest, it can clearly be seen that due to the highest building in the area (the Bursa Ulu Mosque (43 m in height)), a downdraught effect occurred (Figure 5). This effect results in relatively uncomfortable areas in front of the mosque.

When choosing the east wind direction and showing streamlines going through the point of interest, it can clearly be seen that the high-wind (darker color) regions at the corner of the mosque are caused by the pressure difference generated by the obstruction effect of the large mosque facade in the upcoming wind direction (Figure 6).

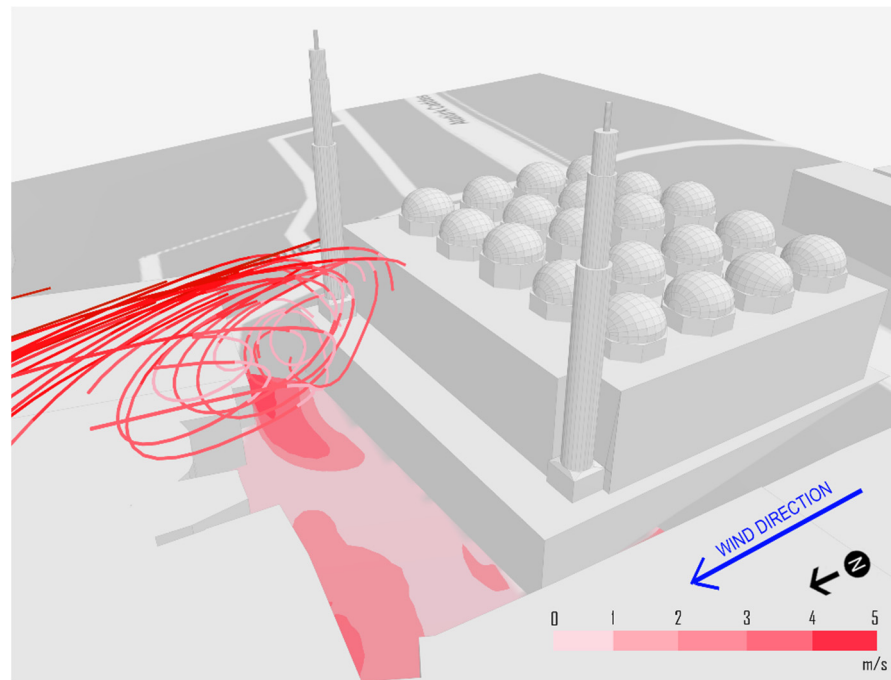


Figure 5. The downdraft effect caused by Bursa Ulu Mosque (analyzed by OpenFOAM v2312 for the south wind direction).

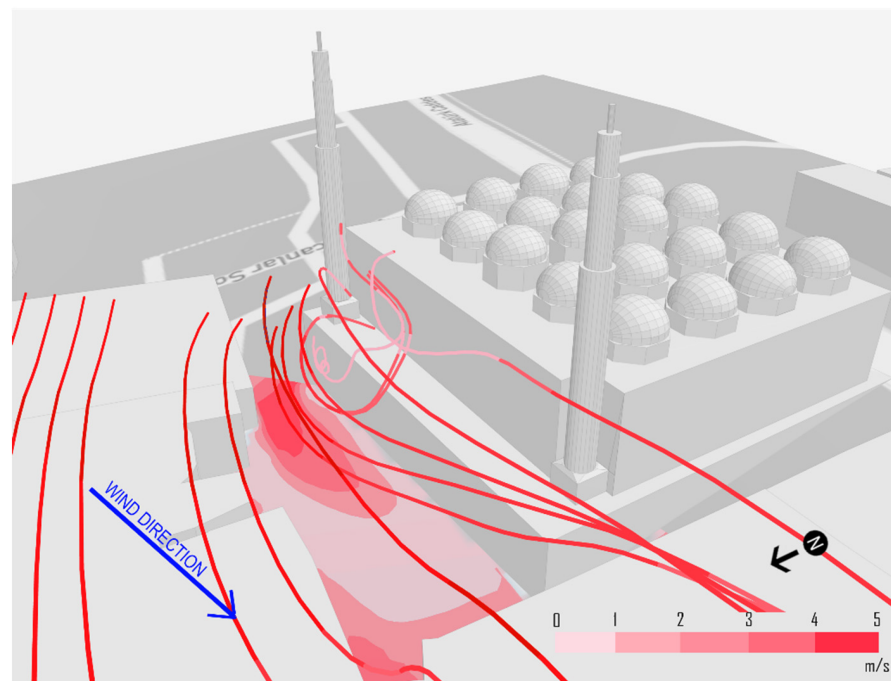


Figure 6. The downdraft effect caused by Bursa Ulu Mosque (analyzed by OpenFOAM v2312 for the east wind direction).

Moreover, the upwards deflection effect can be seen in the wake of the buildings near Cemal Nadir Street. The leeward side of the buildings mostly have negative pressure fields with vortices, which can be seen in Figure 7. In addition, this area is also open to wind effects as it has no obstructions to shield the upcoming wind.

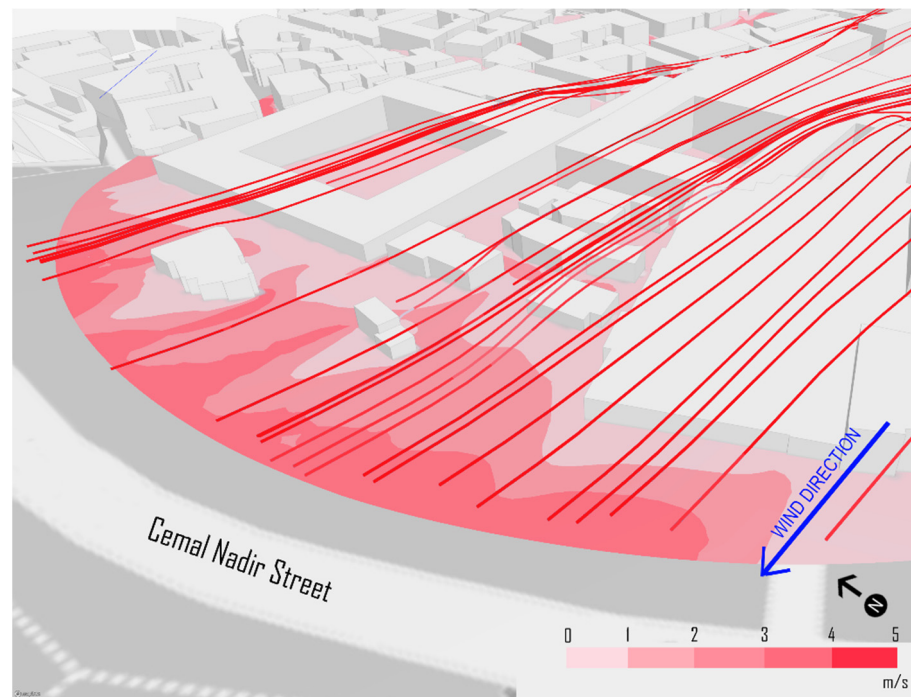


Figure 7. The upwards deflection effect is seen in the wake of the buildings near Cemal Nadir Street (analyzed by OpenFOAM v2312 for the east wind direction).

4.2. Results of the ML-Based Analysis

ML-based analysis is often conducted with the aim of providing guidance in the early design process. The analysis runs instantly and provides wind simulation results reflecting how the wind conditions change based on the design. The rapid wind results are based on predictions and, therefore, are more directional than those of the simulation-based detailed analysis. Therefore, such approaches are mostly used as a tool in the early steps of architectural design.

To see an immediate indication of how the building masses in the case study area impact the wind conditions, an ML-based analysis was conducted. It is clear that instant feedback allows one to see the comfortable and uncomfortable areas easily (Figure 8). Similar to the CFD results, a relatively uncomfortable area (colored in yellow), which is not suitable for sitting or standing activities, can be seen near Cemal Nadir Street. However, the size of this area is comparatively bigger than the one in the CFD results. This may be due to the dataset used for the training process of the ML-based analysis tool. In other words, the dataset may have been prepared in such a way as to stay on the safe side, which may cause the percentage of uncomfortable areas to be higher than expected. The remaining site study area is mostly suitable for sitting and standing, which conforms to the CFD results. However, the uncomfortable area which can be clearly seen near the Bursa Ulu Mosque in the CFD analysis results is not visible in the ML output. This may indicate that the machine-learning-based approach is not sensitive enough to capture such fine details; however, it should be noted that many more comparisons will be needed in future studies to confirm this speculation.

Finally, as indicated above, this tool has limited functionality. The output provided by Autodesk Forma is only an image file; in other words, there is no numerical output. This is why an image-based comparison method was implemented.

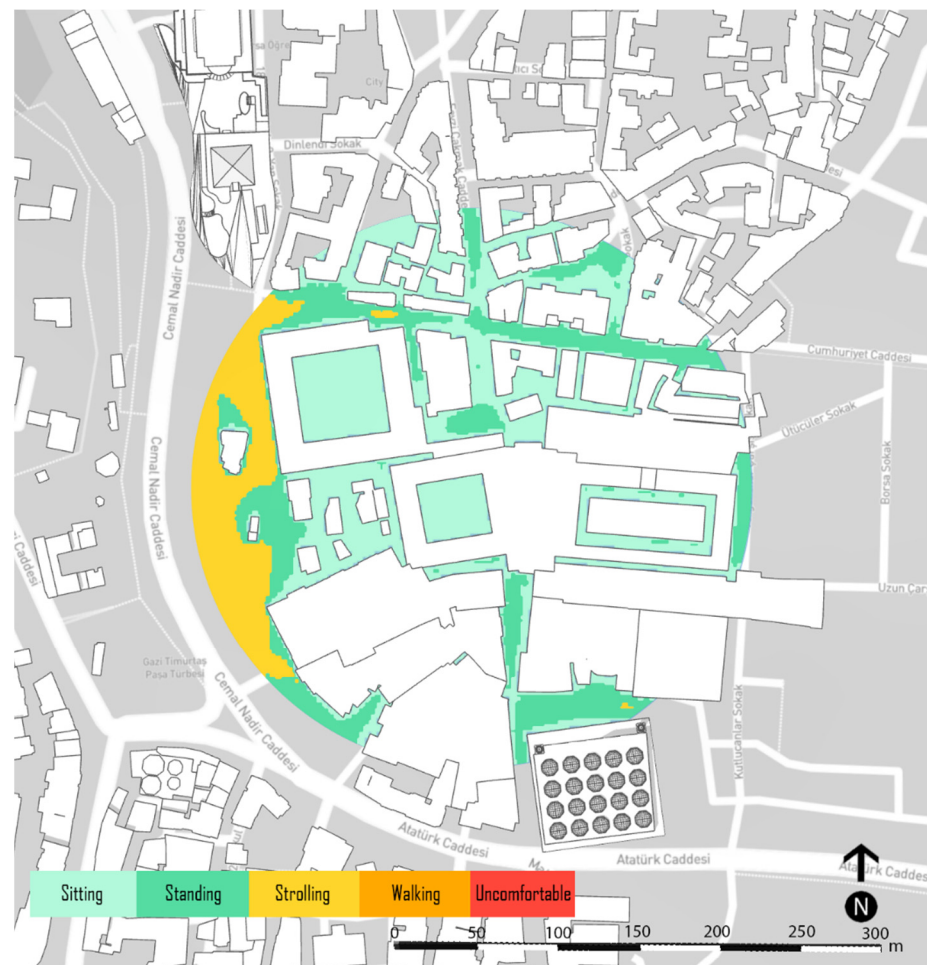


Figure 8. Pedestrian-level wind comfort analysis of the case study area using an ML-based tool (Autodesk Forma ML-based analysis).

4.3. Comparison of the CFD Analysis with ML Based Analysis

In this section, we provide a qualitative assessment of the outputs produced by our machine learning (ML) model, complemented by several evaluation metrics in order to quantify its performance more rigorously. These metrics include the Structural Similarity Index (SSIM), the Mean Square Error (MSE), and the Peak Signal-to-Noise Ratio (PSNR), which are commonly used in the field for assessing image quality and similarity.

Due to the limitation of the Autodesk Forma ML-based analysis tool in terms of it not being able to directly generate a numerical output, we resort to image-based comparison metrics. To facilitate an objective comparison between the target and the generated images, we deliberately introduce specific types of degradations to the target images, namely, adding noise and altering contrast. These operations are crucial for evaluating the robustness and accuracy of our model under varied image conditions, which are common in real-world scenarios.

Noise Introduction: Noise refers to random variations of brightness or color information in images, which can originate from various sources such as sensor imperfections or environmental conditions during image capture. In the context of our study, “target image with noise” simulates the effect of such imperfections in CFD images. Through introducing synthetic noise to the target images, we aimed to test the model’s ability to preserve image quality and structural integrity in the presence of such disturbances, which were quantified using the PSNR and MSE metrics.

Contrast Adjustment: Contrast in images pertains to the difference in luminance or color that makes an object distinguishable. Using “target image with contrast”, we adjust

the contrast levels of the CFD images to evaluate the model's performance in terms of maintaining visibility and differentiation of features under varying lighting conditions. This adjustment is particularly relevant for CFD images, as differences in fluid dynamics properties (e.g., pressure and velocity fields) are often represented by gradients of color or intensity. The SSIM metric is especially useful here, as it assesses how well the structural information is preserved post-contrast adjustment, relative to the original image.

The degradation operations were implemented using a Python script, as detailed in the methodology chapter. These operations not only provide a means to quantitatively assess the ML model's performance using PSNR, MSE, and SSIM, but also simulate real-world challenges that the model might encounter, thus ensuring a comprehensive evaluation of its capabilities. The output of the CFD analysis was accepted as the "target image" for comparison purposes. Both CFD analysis and ML-based analysis outputs were processed to include only wind comfort maps. In other words, site map layers including topography and buildings were excluded from the images, thus enabling an objective comparison. Otherwise, due to the same site map layers, there would be many identical pixels which would result in the comparison of identical pairs. This would result in a higher percentage of similarity than in reality. Taking this fact into consideration, the comparison results are illustrated in Figure 9.

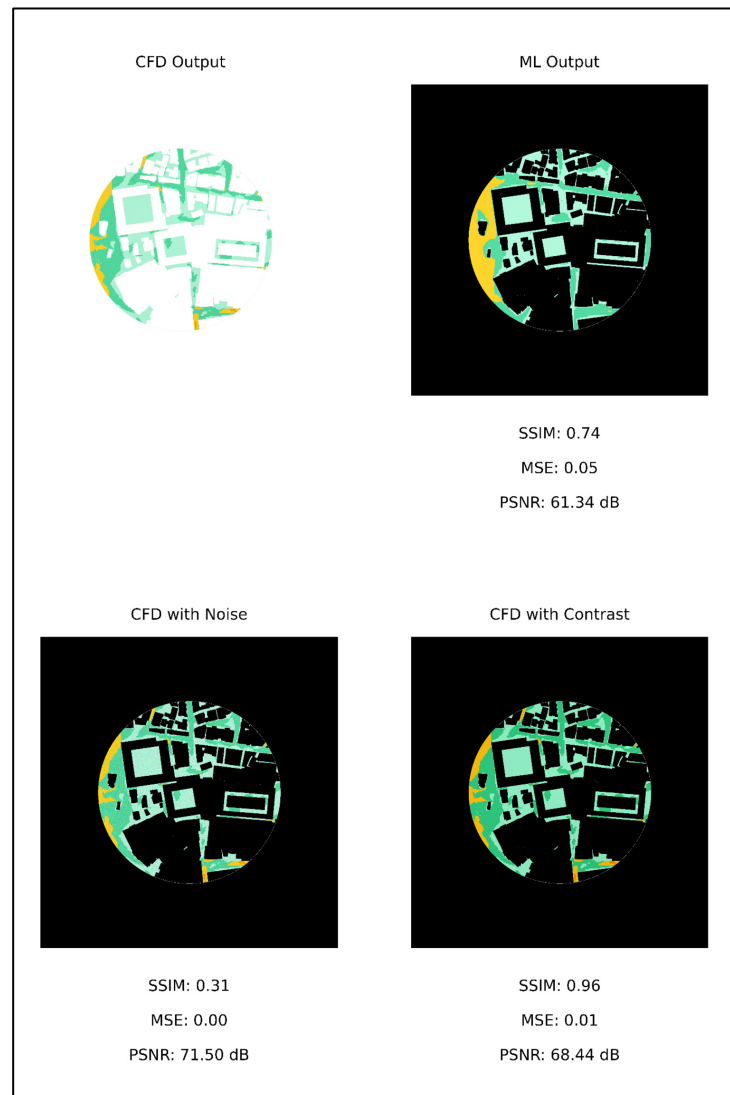


Figure 9. Comparison of the CFD analysis with ML-based analysis using image-based comparison metrics (PSNR, MSE, and SSIM).

The outputs from computational fluid dynamics (CFD) and machine learning (ML) approaches exhibited remarkable similarity, as evidenced by the SSIM metric indicating a similarity of 0.74, the MSE metric showing a similarity of 0.05, and the PSNR demonstrating a similarity of 61.34 dB. However, it is essential to recognize that this evaluation is pixel-based, highlighting a previously mentioned limitation of this study. Nonetheless, the results on the ML side are promising, particularly considering its rapid output speed (in the order of milliseconds), suggesting significant potential for success in preliminary design phase analyses.

5. Discussion and Limitations of the Study

An important topic to discuss is that the dataset used to train the Autodesk Forma ML model is not accessible to users. This is because the ML model embedded in Autodesk Forma was not trained once on a static dataset that can be distributed. Instead, the dataset has an evolutionary format, being continuously fed through user input and subsequently used for re-training the ML model. Consequently, the dataset is constantly changing and contains user data, making it unsuitable for distribution. For ongoing validation, a similar approach was employed: the model was validated by running the surrogate model when a wind analysis was performed and comparing the results. This ensures that the model remains relevant to the current usage of Autodesk Forma, particularly in terms of how buildings and sites/surroundings are modeled. Consequently, the surrogate models provide more up-to-date and contextually accurate approximations of wind analyses, rather than independent machine learning models. Therefore, considering these models outside of their embedded context may not be effective. However, the diversity and representativeness of the model are maintained, as it continuously integrates numerous user outputs, including various urban scenarios and climatic conditions.

On the other hand, it is important to discuss our results in comparison with state-of-the-art models. In the context of using ML for estimating pedestrian-level wind comfort, to the best of our knowledge, InFraRed and Orbital Stack AI are the only other ML models besides Autodesk Forma. According to Kabosava et al. [98], the InFraRed algorithm disregards terrain morphology, meaning that it is only applicable to flat surfaces. Additionally, the comfort metric used in its outputs is unclear, and there is no mention of whether custom weather files can be utilized for simulation. Furthermore, InFraRed is not yet publicly available. These limitations hinder a direct comparison of our results with those of InFraRed.

Similarly, Orbital Stack AI also aims to simulate pedestrian-level wind comfort. However, there are no scientific publications detailing its performance or the specific machine learning methods that it employs. Based on information from the help section of Orbital Stack AI, it appears to produce only visual outputs with a different color legend than Autodesk Forma. Additionally, running simulations with a custom weather file in Orbital Stack AI requires a TC360 format weather file—a format specific to Orbital Stack AI that must be created from scratch [56]. In contrast, Autodesk Forma accepts the widely used EPW (EnergyPlus Weather) files for simulations. Due to these differences, it is not feasible to directly compare the results of Orbital Stack AI with those of Autodesk Forma.

Another important discussion point is the metrics used for comparing the ML predictions with CFD analysis results. As referenced in the methods section [94–97], SSIM, MSE, and PSNR have been widely used for image comparison and processing within machine learning contexts. These metrics provide valuable insights into the visual similarity and quantitative accuracy of images. Although these metrics are not specifically designed for comparing wind analysis results, they can still serve as valuable tools in evaluating general airflow characteristics and trends. To achieve a more specific evaluation of aerodynamic simulations in practical environments, future studies could explore the addition of complementary metrics.

6. Conclusions

The study investigated the application of machine learning (ML) and computational fluid dynamics (CFD) to assess pedestrian wind comfort, particularly for the case of a historical site. As urban areas continue to grow and face the challenges posed by climate change, our study underscores the importance of innovative environmental analysis approaches in creating sustainable, comfortable, and livable cities. Therefore, a comparative analysis of wind estimation techniques was conducted.

Moreover, we aimed to fill a research gap through assessing the efficiency of an ML model in an urban scenario to enhance outdoor wind comfort. Due to the inability of the ML model to produce numerical outcomes at this time, a visual comparison method was required. Using the Structural Similarity Index (SSIM), Mean Square Error (MSE), and Peak Signal-to-Noise Ratio (PSNR) metrics, significant similarity between the machine learning and CFD outputs was observed. The findings demonstrate that machine learning techniques are capable of accurately predicting wind comfort levels up to a level that is nearly comparable to computational fluid dynamics simulations. Moreover, the potential significance of machine learning models in the early phases of architectural design is underscored by their ability to analyze data in milliseconds or less, enabling efficient and rapid assessments of pedestrian level wind comfort.

Besides proposing a methodology for conducting wind comfort studies in urban areas, the study's significant and innovative contribution lies in its unique handling of image data, specifically in enabling an accurate comparison between two visual outputs when numerical data is unavailable. This is important as the sole dependence on visual outputs generated by ML models poses a difficulty, requiring the creation of methodologies that are capable of accurately comparing these outputs with conventional CFD outcomes in the absence of numerical data. Although visual comparison methods are not new, within the scope of the study, the state of the art has been shifted specifically to this field and is accompanied by a new technique. In particular, through the utilization of the alpha channel to discriminate against transparent pixels, the proposed technique ensures that the similarity assessments are grounded in the meaningful content of the images. This methodology is thought to be invaluable in ML-based applications as the images generated may display areas of transparency or experience noise and contrast modifications, which have the potential to distort conventional pixel-based comparison metrics. In other words, the proposed approach enables more objective and relevant comparisons, as it is clear of such distortions.

In conclusion, this study effectively demonstrated the significant potential of integrating ML as a promising complementary tool for the assessment of wind comfort without significant loss in accuracy or detail. The application of machine learning (ML) to urban wind comfort analysis opens up new possibilities for architectural and urban design. In particular, it can be used to quickly assess the wind comfort of outdoor spaces in heritage sites, providing an early but rapid alternative to more in-depth computational fluid dynamics (CFD) studies. Enhancing pedestrian comfort in historic areas is crucial for both urban and tourist users as the spatial experience in these areas is primarily focused on open spaces.

Further investigation should attempt to improve upon these machine learning models through extending their functionalities to incorporate numerical outputs, thereby achieving an output that is easy to compare and surpasses pixel-based metrics. This research attempts to enhance the current knowledge in this subject and introduces new possibilities for creative solutions to intricate urban design and analysis problems. The implications of this study suggest a paradigm shift in how urban planners and architects approach the challenge of designing wind-comfortable outdoor spaces, proposing a more data-driven and technology-enabled process. However, the proposed comparison methodology should be tested by other researchers on different case studies, and its effectiveness should be verified. This will ultimately contribute to the development of more comfortable and sustainable urban environments through not only improving the precision and dependability of ML-based analyses but also expanding their utility in the design and analysis process.

Additional studies can be carried out to compare machine learning with in situ measurements and wind tunnel experiments. Further research is recommended to investigate the incorporation of machine learning models with climate data predictions for climate change, broadening the focus of wind comfort studies to include wider climatic and urban factors. For future research, it is also recommended to broaden the scope of the study beyond wind comfort analysis. Addressing the impacts of other environmental factors and investigating the scalability of the proposed method would be beneficial. This expansion could enhance the applicability and relevance of the research findings to a wider range of environmental analyses.

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