Smart Urban City Building Criteria Based on Carbon Footprint of Individuals Using Deep Neural Network

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ABSTRACT: The definition of an urban city is a highly populated place that also has a large concentration of non-farming jobs, buildings, and infrastructure. Structures such as homes, businesses, roads, and transportation networks make up its built environment. Rural regions are often characterized by lower population densities and an increased dependence on agriculture, in contrast to urban areas. There are more people per unit of land area in urban areas than in rural ones. In addition, man-made structures and vast infrastructure characterize urban areas. Because of this, many city dwellers work in professions unrelated to rural areas. Thus, to design an urbanism city, one should consider the carbon footprint. Various works were achieved to predict the carbon footprint emission. In this work, a deep neural network (DNN) was suggested to predict the carbon footprint in urban cities. The proposed DNN consisting mainly of three dense layers, with other layers such as activation layers and normalization. Results show that the suggested model performs well in predicting carbon footprint with R^2-score equals to 0.5. The utilized dataset in this work is available online at Kaggle.com, and it is well balanced, therefore, there will be no need to do balancing operations. Hence, the trained model can be utilized in urban cities as a robust design tool.

KEYWORDS: Urban Cities, carbon footprint, deep neural network, Keyword3, Keyword4, Keyword5

I. INTRODUCTION

The art of urban planning depends on many factors, including reducing greenhouse gas emissions, as reducing greenhouse gases is one of the important factors in building smart cities with an urban design that achieves sustainable development goals 17. The challenge for most nations is figuring out how to implement a reasonable form of urban governance that will improve the ecological condition of cities for both living and producing. To address this issue, "smart cities" have recently gained popularity as a policy for urban governance on a global scale. Massive increases in urbanization in the last several decades have had far-reaching effects on ecosystems and human health, particularly in terms of emissions of greenhouse gases [1]. Concerns about air pollution and global warming are front and center in the Sustainable Development Goals (SDGs) pertaining to intelligent urban planning and community development. Energy supply chains (SC) in smart cities can become less reliant on fossil fuels with the help of technology and good management. Reduced carbon emissions and a sustainable smart city are the result of well-coordinated technological and managerial efforts supported by suitable infrastructure [2].

Therefore, a number of issues are being magnified in modern cities as a result of population growth brought about by unchecked migration. The only way to solve this problem is to meet the UN's sustainability goals for 2030 and 2050, which include lowering emissions of greenhouse gases (GHG) and adapting to a changing climate [3]. Consequently, carbon emission is the principal design component of urban smart cities. This work will employ deep neural network (DNN) algorithm to make an accurate prediction of carbon footprint, which is helpful in urban cities designing. That is, the prediction will be achieved with respect to the individual’s carbon emission due to the daily life activities, such as transportation type, number of working hours, home energy consumption, number of walked steps, charging station usage, and other factors which will be explained later.

The rest of this work is organized as follows: the next section, section 2, will discuss the related work of the carbon footprint prediction, next section, section 3, is dedicated to discuss the employed dataset and its exploration, section 4 will show the suggested carbon footprint DNN algorithm, then, section 5 will discuss the results, last but not least, the concluding remarks will be drawn in section 6.

II. RELATED WORK OF URBAN SMART CITIES FOOTPRINT

The rapid rise in world temperature is due in part to what is known as the "Enhanced Greenhouse Effect," which is a natural phenomenon that has been amplified by human-caused greenhouse gas emissions. This factor has the potential to hasten unfavorable outcomes, such as global warming. The ability of greenhouse gases to warm the atmosphere varies amongst them, depending on factors such as the radiative power they emit and the average atmospheric lifetime of their molecules [4].

Nowadays, cities and residential areas are incredibly technologically and digitally advanced. As a result of data analytics, old infrastructure and equipment are now being upgraded to improve their performance [5]. Technological progress, then, is the cause of complicated sociocultural shifts. It is widely acknowledged that there is a need to reduce environmental and climatic impacts, especially carbon footprint., in order to provide cleaner energy sources or more efficient energy services, as countries are taking action against climate change and closely monitoring its environmental effects [5].

Using Xiamen as an example, the authors of [6] establish an estimation approach for quantifying the carbon footprint of urban construction projects. The possibility of reducing emissions is also investigated through a scenario analysis. In Xiamen, the carbon footprint of urban buildings grew at an average yearly rate of 12.87%, going from 8.95 million tons in 2005 to 13.57 million tons in 2009. The production of building materials was responsible for 45% of the building's carbon footprint, while the use of building energy was responsible for 40%.

Utilization of energy and emission levels of carbon have risen dramatically due to urbanization, but these problems are reversible with well-planned and managed cities. However, machine learning (ML) and deep neural networks (DNNs) have gained a wide range of applications, such as in security [7], sport field [8], urban city design [9], medicine [10] [11] [12], and many other applications. Thus, since this work will build a DNN model for carbon footprint prediction, we will bring the most significant related works in this section. For instance, using deep reinforcement learning (DRL), Shen et al. [13] suggest a bottom-up approach to reduce urban carbon emissions.

In order to build a complete model of urban carbon emissions, they use Ningbo City as an example and combine data from multiple urban sources, such as the urban transportation system and points of interest (POIs), with different carbon emission coefficients for various forms of transportation. In order to reduce carbon emissions from transportation, the suggested DRL model uses an Actor-Critic architecture to optimize the ratio of different types of buildings to land use within an urban matrix repeatedly.

In order to evaluate the sustainability of urban areas, Zhang et al. [14] created a set of indicators that includes urban ecological energy, shifts in land utilization, population growth, environmental offerings, habitat integrity, boosted plant index, greenhouse gases, and the accumulation of carbon.

The durable condition of Xuzhou City (in China also) from 2020 to 2050 is projected using a neural network that uses a dataset from 2000 to 2020 to forecast energy indicators for sustainability over a time series. Nevertheless, when it comes to the dynamics and patterns of urban climate, greenhouse gases are crucial.

The use of ML techniques presents potential for the present and future prediction of urban greenhouse gas emissions. In [15], they take a look at 75 articles published between 2003 and 2023 that predicted emissions of greenhouse gases from cities using ML. Note that to guide climate mitigation efforts, it is essential to assess the future warming impact of food consumption, which is a key contributor to greenhouse gas emissions.

The broad use of simplified metrics like CO2 equivalents and the absence of detail in reporting emissions from food items make interpretation difficult. It is found that just the world's food consumption could increase global warming by almost 1 degree Celsius by the year 2100. Ruminant meat, dairy, and rice are the three main culprits responsible for 75% of this warming. Nevertheless, if production methods are improved, everyone should eat healthily, and food waste is reduced at the consumer and retail levels, we can prevent more than half of the predicted warming [16]. This should be considered honestly in urban cities basic structure.

Using data collected from practically every European Municipality between 2001 and 2018, the authors of [17] create a scalable and replicable ML method based on an extreme gradient boosting model to assess the effectiveness of mitigation projects. They forecast yearly carbon dioxide emissions to investigate patterns in mitigation performance at the city scale by integrating publicly available, spatially explicit demographic and environmental information with self-reported pollution data from European cities.

In their work [18], Wen and Liu provide a practical model for analyzing the factors influencing Beijing's carbon emissions and making predictions about what's to come. The work optimizes the initial connection weights and thresholds of the traditional belief propagation neural network using the non-inertia weight coefficient and particle mutation particle swarm optimization (PSO) algorithm. It then builds a model of the network based on the enhanced PSO. On the other hand, in order to establish a connection between 18 preliminary indicators and CO2 emissions, grey relational analysis was used in [19].

Support vector machines (SVMs) rely on principal component analysis to sift through large amounts of data and identify its four primary components for use in making predictions. An improved version of the chicken swarm optimization (ICSO) algorithm, called ICSO-SVM from here on out, is suggested for optimizing SVM parameters by incorporating chaotic mutation and a nonlinear weight index.

Lastly, CO_2 emissions from Shanghai, China, homes that are connected to energy use are predicted using the novel hybrid model.

As indicated previously, DNN model will be suggested to predict carbon footprint in this work, based on daily life activities of human. This might be more understood if one understands the dataset to be employed to learn the suggested DNN model. The next section will discuss the adopted dataset for this job.

III. EXPLORATION OF DATASET AND PREPROCESSING

A futuristic and urbanism smart city's inhabitants' everyday lives are mapped out in great detail in this dataset. The dataset is available online at Kaggle.com (Futuristic Smart City Citizen Activity Dataset), which can be reached using this link: https://www.kaggle.com/datasets/atharvasoundankar/futuristic-smart-city-citizen-activity-dataset.

The above dataset covers various aspects such as the Demographics information, in terms of age and gender, the transportation method, such as mode of transportation and the number of walked steps. Furthermore, the dataset involves the working hours which is a term of lifestyle besides the social engagement that include: shopping, social media utilization, and the entertainment.

Moreover, the health and wellbeing are also included such as the calories burned and the number of sleeping hours. Nevertheless, the energy consumption in home is also included as an energy feature. The carbon footprint and the stations of charging utilization are included in the sustainability features part of the dataset. Urban mobility, sustainability, health trends, and behavioral analytics are some of the areas that could benefit from this 1000-row, 15-column dataset for data analysis, ML, and visualization projects.

In more depth, the dataset includes: the age 'Age', sex 'Gender', transportation class 'Mode_of_Transportation', number of working hours 'Work_Hours', number of shopping hours 'Shopping_Hours', the entertainment hours 'Entertainment_Hours', the energy consumption in the individual's home in kilo Watts/hour (kWh) 'Home_Energy_Consumption_kWh', the utilization of the charging stations, since it is an urban smart city 'Charging_Station_Usage', the carbon footprint in kilogram of CO2 (kgCO2) 'Carbon_Footprint_kgCO2', number or amount of steps walked by the individual 'Steps_Walked', burned calories by individuals 'Calories_Burned', resting hours such as sleeping 'Sleep_Hours', hours spent for social media 'Social_Media_Hours', and the number of hours spent for public events 'Public_Events_Hours'.

Table 1 lists the distributions (ranges) of the abovementioned features as well as the units of measures for each feature, where there are some features have different modes, such as numerical values and strings (text) values.

TABLE I
DATASET FEATURES DESCRIPTION AND DISTRIBUTIONS

FEATURE	DESCRIPTION
Age	Between 18 and 69 years
Gender	Male, Female, and others
Transportation	Walking, Bike, Car, Electric Vehicle, Public, other
Work-Hours	Zero to 9-hours
Shopping-Hours	Zero to 4-hours
Entertainment-Hours	Zero to 3-hours
Energy Consumption	Between 2 and 9.99 hours
Charging Station-Usage	Zero to 1-hour
Carbon-Footprint	Between 10.02 to 99.93 (kgCO2)
Steps-Walked	From 1011 to 19972
Calories-Burned	171 to 1447
Sleep-Hours	4 to 10-hors
Social Media-Hours	Zero to 6-hours
Public Events-Hours	Zero to 3-hours

That is, the age is ranged between 18-years old (counts to 119 persons) and 69-years old (counts to 129 persons) with average of 44-years old. The transportation mode was categorized into six types: Walking, Bike, Car, Electric Vehicle (EV), Public, and others.

However, Figure 1 shows the gender distribution, where the male/female are balanced, therefore, the other category will be dropped out, while Figure 2 shows the age distribution, which is as illustrated in Table 1, the age is between 18 years old and 69 years old.

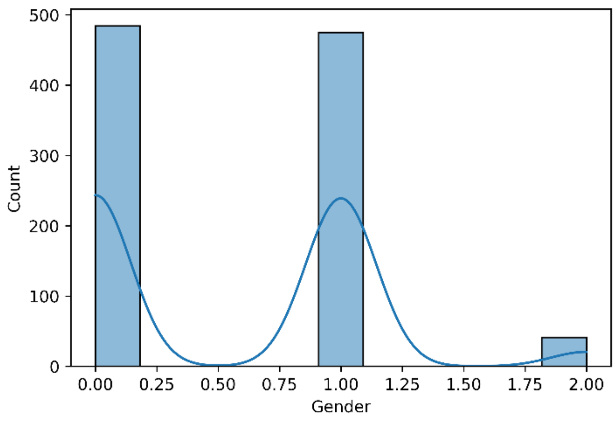

FIGURE 1. Gender distribution in the adopted dataset

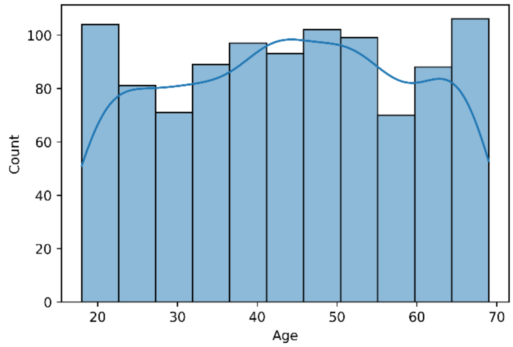

FIGURE 2. Age distribution as in Table 1

There are six-transportation modes: Walking, Bike, Car, Electric Vehicle, Public, other, the distribution of these modes is shown in Figure 3. All of the modes are almost balanced, therefore, there is no need to do a balancing operation to this feature.

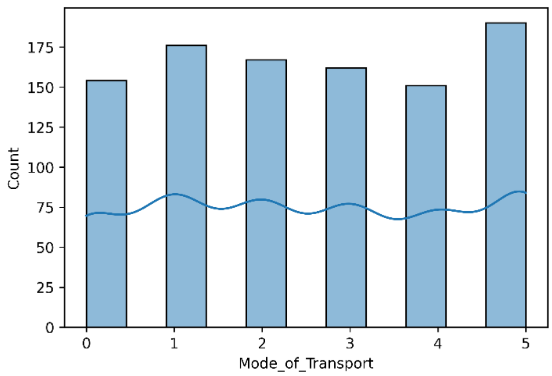

FIGURE 3. Transportation distribution as in Table 1 of the adopted dataset

Note that Table 1 shows that the working hours are between zero to 9-hours, however, Figure 4 shows the working hours distribution. It can be seen that there is no 5-hours exists in the dataset as working hours.

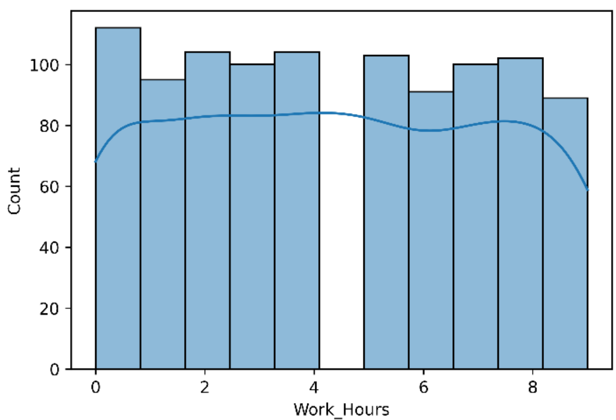

FIGURE 4. Working hours of the individuals during the working days

Shopping hours, per each single day for each individual, are distributed between zero to four-hours, as shown in Figure 5. The majority is clearly nearly four-hours then two-hours. However, the feature is well balanced and do not need to be re-balanced.

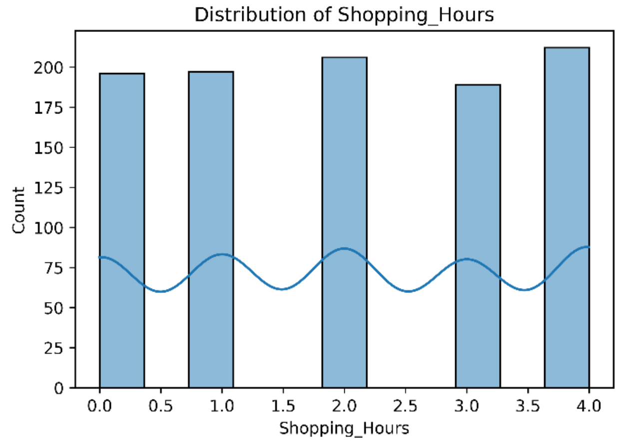

FIGURE 5. Distribution of the shopping hours

The same attitude of the shopping hours was captured in the entertainment hours with only one difference, which is the maximum entertainment hours are 3, as shown in Figure 6. Nevertheless, Figure 7 shows the energy consumption per unit area (one house/home) for the individuals. The consumed energy was measured in kWh. The minimum consumed energy was 2kWh, while the maximum consumption was 9.99kWh, as listed in Table 1 and as shown in Figure 7. However, in Figure 7, the magnitude 9.99kWh was approximated to 10kWh for convenience.

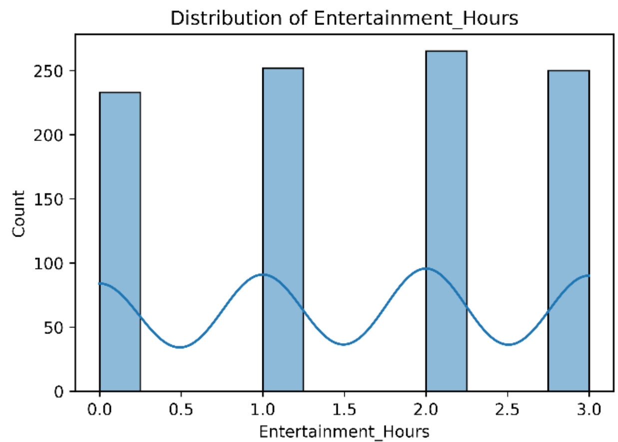

FIGURE 6. Distribution of the entertainment hours

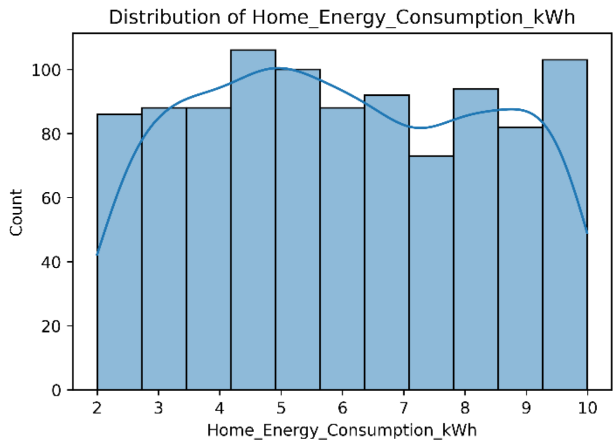

FIGURE 7. Distribution of the energy consumption in kWh per home

It seems that charging stations was not utilized extensively. This is clearly observed in Table 1 and can be confirmed in Figure 8, where most of the entries show zero charging hours (70%), while only 30% were use the power charging stations. This leads to deduce that few individuals are owned electric cars, which is confirmed in Figure 4, where x-axis index number 4 stands for electric cars.

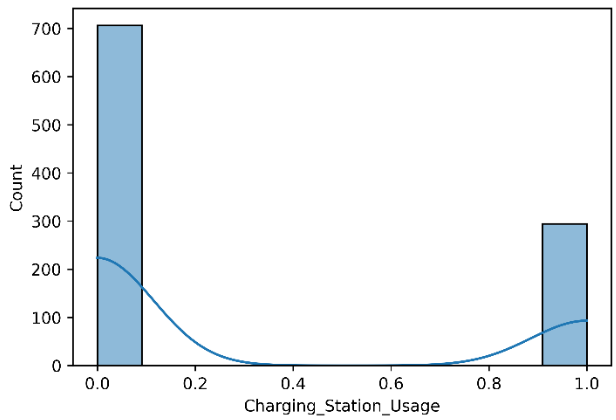

FIGURE 8. Distribution of the charging station utilizations

Carbon footprint distribution is shown in Figure 9, where it can be observed that most of the occurrence is between 50 to 60 kgCO2, where it is shown in Table 1 that the carbon footprint is from 10.02 to 99.93 kgCO2.

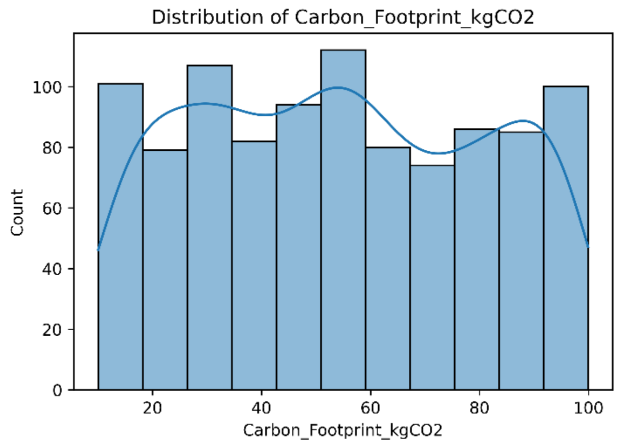

FIGURE 9. Distribution of the carbon footprint

Figure 10 shows that most individuals prefer to use walking as an entertainment or as a transportation mode, this is because the maximum walking hours of 20k-steps was dominated.

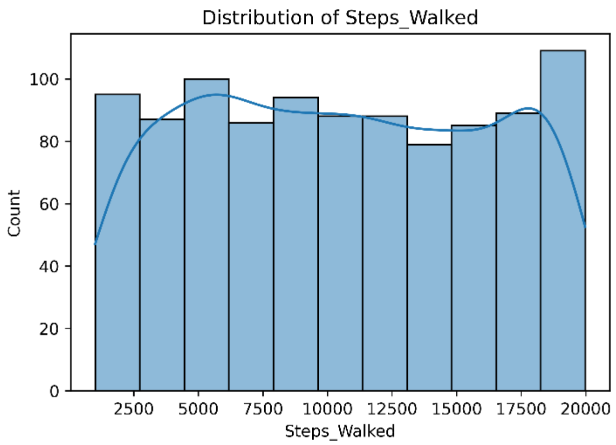

FIGURE 10. Distribution of the walking steps of the individuals

Normal distribution was captured in Figure 11 for the feature 'Burned_Calories', which is the only feature in the dataset that behaved in this fashion. Figures 12-14 show the sleeping hours, social media hours, and public events hours distributions. The behaviors of these distributions do not have much difference with the previous distributions of the features, which are stated previously in Table 1.

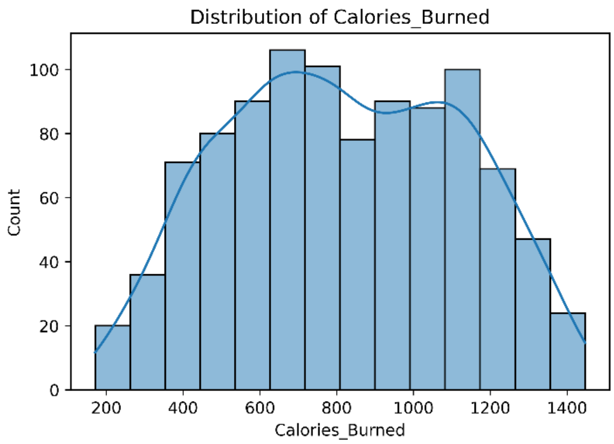

FIGURE 11. Distribution of the burned calories

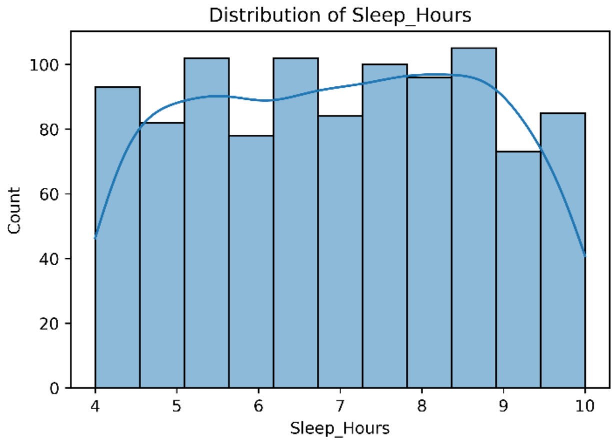

FIGURE 12. Distribution of the sleeping hours

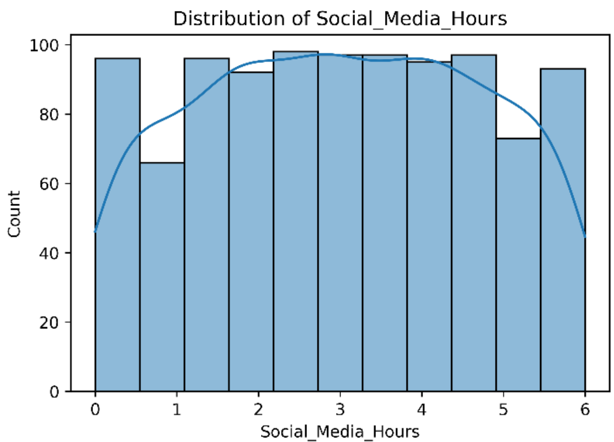

FIGURE 13. Distribution of the spent hours on the social media

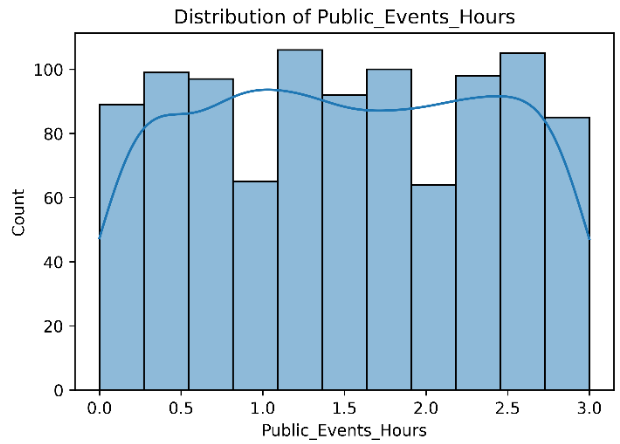

FIGURE 14. Distribution of the spent hours on the public events

That is, the dataset is properly balanced. Then, it is ready to be cleaned from nulls and not logical values, as a pre-processing before make use of it. After cleaning, the dataset will be split into training set, 70%, testing set, 20%, and validation set, 10%. The dataset now is ready to be used to train the suggested model in the next section.

IV. DEEP NEURAL NETWORK SUGGESTED MODEL

The suggested model in this work is based on fully connected, dense, layers. Figure 15 shows that the suggested model is basically consisting of three dense layers, the first one is consisted of 64-points, next dense layer is constructed from 32-points, and the last one includes only one point, since it is a regression operation, therefore, we need only one point at the output of the model.

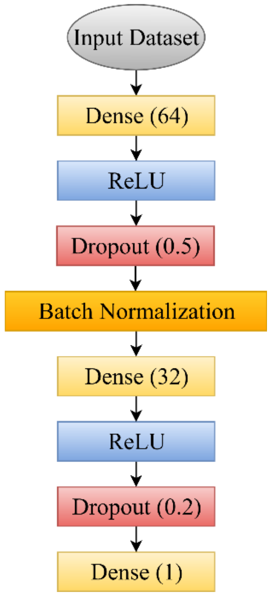

FIGURE 15. correlation coefficient of predictor values

However, after the first dense layer, there is an activation layer, which is rectified linear unit that will add non-linearity to the model. Since there are some entries of the dataset that can be considered as outliers, the model should focus on the most dominated entries, therefore, a dropout layer of 50%-dropping probability was added. After the dropout layer, the next layer was batch normalization, to make the training process smoother. Now, the second dense layer, which is of 32-points, is added. An activation function should be used following the dense layer, and then a dropout layer of 20% probability was used. Last but not least, the output dense layer of one-point was attached at the end of the model. Table 2 shows the list of the layers that employed in Figure 15 with total number of learnable parameters of each layer.

TABLE II
LEARNABLE PARAMETERS OF THE SUGGESTED MODEL

Layer Type	Output Shape	No. Parameters
Dense	64	896
Drop Out	64	0
Batch Normalization	64	256
Dense	32	2080
Drop Out	32	0
Dense	1	33
Total		**3265**

That is, there are 3265 learnable parameters in the suggested model. Not all of these 3265 parameters will be trained, where there are 128 parameters will not be trained. In other words, there are 3137 trainable params in our suggested DNN model. The next section will discuss the other parameters that are necessary to train the model, i.e., the hyperparameters, and show the output results after training phase.

V. RESULTS AND DISCUSSION

As discussed in the last section, the suggested model in this work is based on fully connected layers and it includes other layers such as ReLU, dropout, and batch normalization layers. However, it is essential to mention here that the model was build and trained using a personal computer with 12th Gen Intel(R) Core-i7-1255U, 1.70 GHz, 16.0 GB-RAM, windows 64-bit operating system. Consequently, hyperparameters were set as follows: the training set is 70%, testing set was 20%, and the validation set was 10% of the total dataset. Adaptive Moment Estimation (adam) was adopted as the optimizer; the loss function was a customized version that depends on the absolute value of the error with 125% as a penalty paid to overcome the over/under prediction process. The validation loss value was the monitored parameter during the training operation, with 20-iterations as patience and the model will return the best model during 200 epochs, where the batch size was 32 samples.

According to the abovementioned hyperparameters settings, the DNN suggested model was trained, tested, and validated. Figure 16 shows the training and validation history of the suggested model. It is shown that the best results were captured at epoch number 24, where the minimum loss is 22.9859.

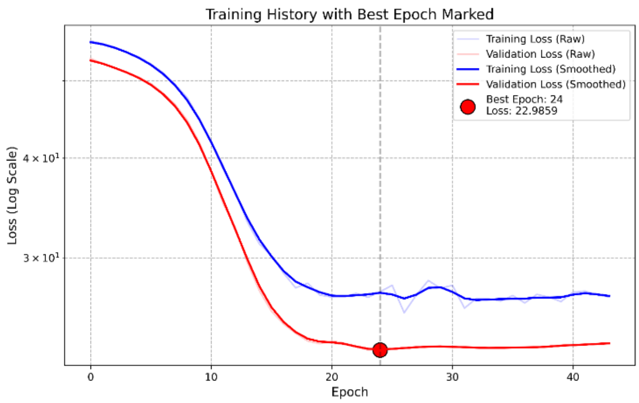

FIGURE 16. Training-validation history of the suggested model based on the discussed hyperparameters.

When it comes to deep analysis of the trained model, the distribution of the prediction errors can be analyzed. Figure 17 shows that the model was well trained, tested, and validated. For instance, the errors are ranged -40 to +60, and the majority of errors cluster between -20 to +40. Note that the zero-error line is in dashed-red colored line in Figure 17.

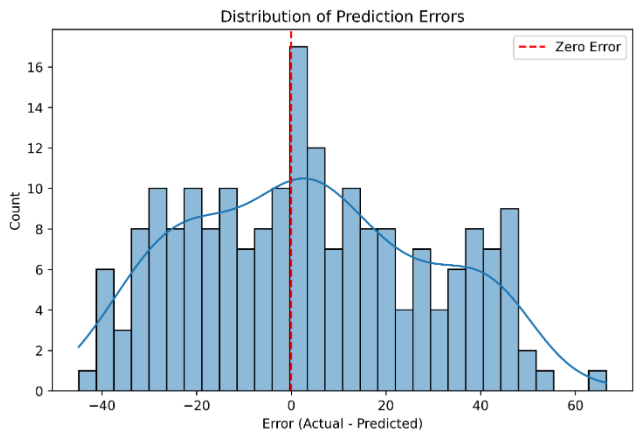

FIGURE 17. Training-validation history of the suggested model based on the discussed hyperparameters.

Moreover, the histogram peak is closer to zero, which represents less systematic overprediction, and the there are no errors beyond ±60. For more convenience, the resultant R^2-Score was almost perfect, 0.5, for the suggested model after training and validation.

VI. CONCLUSION

Urban city design relay on different designing parameters. One of the most important parameters is the carbon footprint. Our suggested model has been able to predict the footprint of the carbon emission, where three dense layers were the main construction layers of the model. Other layers were added to overcome the over/under fitting problems and under/over prediction problems. According to the results, it is recommended to use our model as a robust tool to help in designing urbanism smart cities.

REFERENCES

[1] Y. Shu, N. Deng, Y. Wu, S. Bao, and A. Bie, "Urban governance and sustainable development: The effect of smart city on carbon emission in China," *Technological Forecasting and Social Change,* vol. 193, p. 122643, 2023/08/01/ 2023, doi: https://doi.org/10.1016/j.techfore.2023.122643.

[2] S. B. Issa Zadeh and C. L. Garay-Rondero, "Enhancing Urban Sustainability: Unravelling Carbon Footprint Reduction in Smart Cities through Modern Supply-Chain Measures," *Smart Cities,* vol. 6, no. 6, pp. 3225-3250, 2023. [Online]. Available: https://www.mdpi.com/2624-6511/6/6/143.

[3] G. Halkos and E.-C. Gkampoura, "Where do we stand on the 17 Sustainable Development Goals? An overview on progress," Economic analysis and policy, vol. 70, pp. 94-122, 2021.

[4] R. Brereton, S. Bennett, and I. Mansergh, "Enhanced greenhouse climate change and its potential effect on selected fauna of south-eastern Australia: A trend analysis," Biological Conservation, vol. 72, no. 3, pp. 339-354, 1995/01/01/ 1995, doi: https://doi.org/10.1016/0006-3207(94)00016-J.

[5] W. Hurst, B. Tekinerdogan, and B. Kotze, "Perceptions on Smart Gas Meters in Smart Cities for Reducing the Carbon Footprint," Smart Cities, vol. 3, no. 4, pp. 1173-1186, 2020. [Online]. Available: https://www.mdpi.com/2624-6511/3/4/58.

[6] W. Huang, F. Li, S.-h. Cui, F. Li, L. Huang, and J.-y. Lin, "Carbon Footprint and Carbon Emission Reduction of Urban Buildings: A Case in Xiamen City, China," Procedia Engineering, vol. 198, pp. 1007-1017, 2017/01/01/ 2017, doi: https://doi.org/10.1016/j.proeng.2017.07.146.

[7] E. H. Salman, M. A. Taher, Y. I. Hammadi, O. A. Mahmood, A. Muthanna, and A. Koucheryavy, "An Anomaly Intrusion Detection for High-Density Internet of Things Wireless Communication Network Based Deep Learning Algorithms," *Sensors,* vol. 23, no. 1, p. 206, 2023. [Online]. Available: https://www.mdpi.com/1424-8220/23/1/206.

[8] Ł. A. Gierz, H. S. Mizher, M. A. Taher, B. S. Falih, Ł. Warguła, and B. Wieczorek, "Detecting and classifying media images of athletes using convolutional neural networks: Case study," *Adv. Sci. Technol. Res. J.,* 2025-01-07 2025. [Online]. Available: https://www.astrj.com/Detecting-and-classifying-media-images-of-athletes-using-convolutional-neural-networks,199798,0,2.html.

[9] A. H. A. Hussain *et al.*, "Urban Traffic Flow Estimation System Based on Gated Recurrent Unit Deep Learning Methodology for Internet of Vehicles," *IEEE Access,* vol. 11, pp. 58516-58531, 2023, doi: 10.1109/ACCESS.2023.3270395.

[10] A. Waheed, M. Goyal, D. Gupta, A. Khanna, F. Al-Turjman, and P. R. Pinheiro, "CovidGAN: Data Augmentation Using Auxiliary Classifier GAN for Improved Covid-19 Detection," *IEEE Access*, vol. 8, pp. 91916-91923, 2020, doi: 10.1109/ACCESS.2020.2994762.

[11] Q. Guan, Y. Huang, Z. Zhong, Z. Zheng, L. Zheng, and Y. Yang, "Thorax disease classification with attention guided convolutional neural network," *Pattern Recognition Letters,* vol. 131, pp. 38-45, 2020/03/01/ 2020, doi: https://doi.org/10.1016/j.patrec.2019.11.040.

[12] A. Mabrouk, R. P. Díaz Redondo, A. Dahou, M. Abd Elaziz, and M. Kayed, "Pneumonia Detection on Chest X-ray Images Using Ensemble of Deep Convolutional Neural Networks," *Applied Sciences,* vol. 12, no. 13, p. 6448, 2022. [Online]. Available: https://www.mdpi.com/2076-3417/12/13/6448.

[13] J. Shen, F. Zheng, Y. Ma, W. Deng, and Z. Zhang, "Urban travel carbon emission mitigation approach using deep reinforcement learning," *Scientific Reports,* vol. 14, no. 1, p. 27778, 2024/11/13 2024, doi: 10.1038/s41598-024-79142-3.

[14] C. Zhang, S. Yu, and J. Zhang, "Research on Urban Sustainability Based on Neural Network Models and GIS Methods," *Sustainability*, vol. 17, no. 2, p. 397, 2025. [Online]. Available: https://www.mdpi.com/2071-1050/17/2/397.

[15] Y. Jin and A. Sharifi, "Machine learning for predicting urban greenhouse gas emissions: A systematic literature review," *Renewable and Sustainable Energy Reviews,* vol. 215, p. 115625, 2025/06/01/ 2025, doi: https://doi.org/10.1016/j.rser.2025.115625.

[16] C. C. Ivanovich, T. Sun, D. R. Gordon, and I. B. Ocko, "Future warming from global food consumption," *Nature Climate Change,* vol. 13, no. 3, pp. 297-302, 2023/03/01 2023, doi: 10.1038/s41558-023-01605-8.

[17] A. Hsu, X. Wang, J. Tan, W. Toh, and N. Goyal, "Predicting European cities' climate mitigation performance using machine learning," *Nature Communications,* vol. 13, no. 1, p. 7487, 2022/12/05 2022, doi: 10.1038/s41467-022-35108-5.

[18] L. Wen and Y. Liu, "A research about Beijing's carbon emissions based on the IPSO-BP model," *Environmental Progress & Sustainable Energy,* vol. 36, no. 2, pp. 428-434, 2017, doi: https://doi.org/10.1002/ep.12475.

[19] L. Wen and Y. Cao, "Influencing factors analysis and forecasting of residential energy-related CO2 emissions utilizing optimized support vector machine," *Journal of Cleaner Production,* vol. 250, p. 119492, 2020/03/20/ 2020, doi: https://doi.org/10.1016/j.jclepro.2019.119492.

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