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Predicting On-Street Parking Violation Rate Using Deep Residual Neural Networks

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ABSTRACT

The lack of available parking spaces can be among the most significant issues that can affect the quality of life of citizens in large cities. This has led to the development of on-street parking systems that typically ensure that parking spaces will be available for the local population, as well as provide easy access to parking for visitors, e.g., by providing directions for finding sectors where parking slots are available. Unfortunately, such systems are affected by illegal parking, i.e., parking without paying the parking fee, since in this case, the number of registered parked cars does not match the number of cars that are actually parked, leading to providing incorrect suggestions to drivers. This can discourage drivers from using such systems, potentially further increasing the parking violation rate. Such phenomena can be addressed by using smart sensors that can detect the presence of cars in various areas. However, installing and maintaining such systems is costly, which usually discourage cities from implementing such solutions. The main contribution of this paper is a Deep Learning (DL)-based pipeline that works in an indirect way (i.e., without using sensors) and allows for developing an accurate fine-grained parking violation prediction system, increasing in this way the accuracy of the information provided to on-street parking systems with minimal cost. To deal with missing and noisy data we also propose a data augmentation and smoothing technique that can further improve the accuracy of DL models, when used in such scenarios. The effectiveness of the developed system is validated using experiments on a large-scale dataset, which contains more than 3.9 million scans for illegally parked cars collected by the municipal police in Thessaloniki, Greece.

1. Introduction

Finding available parking spaces in large cities and/or crowded areas, such as in a city's center or near tourist attractions can be very frustrating for drivers. To this end, several intelligent on-street parking systems have been developed and implemented by cities (Vital et al., 2020). These systems usually segment the city into a number of sectors, where each sector typically contains several parking slots. When drivers pay the parking fee, the system is updated to reflect this information allowing for estimating the sectors where free slots are available. This information is then used to update the system with the necessary information regarding the availability of parking spaces. This enabled the development of smart systems that can guide drivers into sectors that have free slots available in real time, significantly reducing the effort of finding available parking slots. Unfortunately, such systems are affected by illegal parking, i.e., parking without paying the parking fee, since in this case parked cars are not registered. As a result, the system has no longer up-to-date information regarding the availability of parking slots and cannot provide useful information to drivers. These phenomena can lead to a significant degradation in the performance of such systems, especially during peak hours. As a result, drivers' trust in the system is reduced, since they are provided with the wrong directions, which can in turn further increase the parking violation rate.

Street occupation sensors can be used to address some of these issues since they allow for detecting whether a car is parked in a specific slot of a sector. These systems usually work either by using street sensors that are buried under the road or by employing more advanced vision-based systems (Yang et al.,

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2017). Despite their benefits, installing such systems usually comes with a significant cost, which can outweigh their benefits. Furthermore, these systems tend to work better in constrained settings, e.g., in closed parking spaces instead of public ones, while installing them in entire cities can be especially challenging. This paper aims to determine whether it is possible to acquire such information using *indirect* measurements, such as location, time, historical patterns, weather information, number of cars already parked, etc. Therefore, we aim to predict illegal parking rates in different parking sectors around a city. This information can allow for upgrading the operation of existing parking systems with minimal costs by providing more accurate information to drivers and providing incentives to use them. The number of available parking slots can be thus estimated by predicting the number of illegally taken slots. This information, along with the number of legally parked cars (which is always available), allows for redirecting drivers towards sectors that are more probable to have free parking slots. Despite the potential of such a system, there are also significant challenges regarding several aspects of its design, ranging from how the input data are gathered and encoded to how the ground truth parking violation data are collected. For example, directly encoding the position of each sector using its GPS location typically leads to suboptimal results. Indeed, this was among the first challenge we faced when trying to represent the geographical place of a sector in a way that would allow DL models to generalize (e.g., global GPS coordinates do not provide any direct information regarding the expected traffic in a sector). This issue can be avoided by using indirect encoding for the position, e.g., by using distances from several Points of Interest (PoI) that usually attract citizens on a frequent basis.

The main contribution of this work is a Deep Learning (DL)-based on-street parking violation prediction system that works integrated with on-street parking systems, as well as an extensive evaluation of the performance of the developed DL models using a large-scale dataset, which contains more than 3.9 million scans for illegally parked cars collected by the municipal police in Thessaloniki, Greece. DL has been shown to outperform other approaches for a wide variety of tasks (LeCun et al., 2015), ranging from license plate recognition (Wang et al., 2020; Selmi et al., 2020) to vehicle detection (Djenouri et al., 2022) and re-identification (Tumrani et al., 2020). Yet applying DL in novel domains is not always easy and it comes with several challenges. Among the main challenges that we face is the existence of sparse annotations, i.e., information regarding illegal parking is only available when the police scan for such cases. This poses significant challenges since annotations can be especially noisy, i.e., having information for a sector but not for neighboring ones. Directly using such information in DL-based systems is challenging, since it is known that DL models can be affected by noisy annotations, which often leads to applying label smoothing and distillation methods to mitigate these effects (Lukasik et al., 2020; Tsantekidis et al., 2020). To address these issues, we developed a novel data smoothing and augmentation approach that assigns existing ground truth annotation to time slots, leading to significant performance improvements. To the best of our knowledge, this is the first time that such an approach is applied in the context of an on-street parking violation prediction system. Other challenges include imprinting input data, such as the geographical location of each sector, time, and other information, such as pandemic measures (i.e., due to COVID-19) in an efficient manner. The performance of the system was validated using extensive experiments, including appropriate ablation studies that demonstrate the effect of various design choices. The code used for the conducted experiments and data samples can be found at `https://github.com/nikgeokar/Parking_Violation_Prediction`.

The rest of the paper is structured as follows. Section 3 introduces the proposed method, detailing all important aspects of data pre-processing and model construction. Then, the experimental evaluation is provided in Section 4. Finally, conclusions are drawn in Section 5.

2. Related Work

In recent years there is an increasing interest in predicting various metrics regarding the behavior of drivers in various parking systems. Most works focus on predicting the number of available parking spaces (Tiedemann et al., 2015; Ye et al., 2020). This typically involves both illegally parked and legally parked cars, while these methods are not able to handle fine-grained parking violation predictions when there is a large number of parking sectors. On the other hand the proposed method focuses on solving a fine-grained variant of the on-street parking violation prediction problem by providing information for hundreds of sectors, handling a different type of problem. Therefore, the proposed method provides an advancement over these approaches, since it allows for providing fine-grained predictions for illegally parked cars, which - in turn - enables the system to provide detailed and up-to-date instructions to drivers for finding available parking spaces. Other works focus on predicting different metrics regarding the behavior of drivers, such as double parking events (Gao and Ozbay, 2017), which concerns a related, yet different type of problem.

The most closely related approach to our method is provided by (Gao et al., 2019), where parking violations are predicted using random forests and existing open data at various spatio-temporal points. To the best of our knowledge, our approach advances the state-of-the-art over this approach by a) including additional input features that can lead to improved prediction accuracy, b) incorporating data augmentation and smoothing for handling missing data and c) allowing the system to work at a sector level, providing outputs that can be readily integrated into the structure of existing on-street parking systems. It should be also noted that these approaches are typically closely-tied to the specifics of each parking system, making direct comparisons difficult without adjustments. However, as we demonstrate in Section 4, the proposed method can indeed lead to improved performance over to the most closely related approach, after appropriately adjusting it to the used setup.

3. Proposed Method

In this section we present the proposed method used for predicting on-street parking violations using DL. First, we introduce the used features, as well as the way the prediction target was compiled using the available data. The impact of the constructed features is also experimentally evaluated in the ablation study provided in Section 4. Then, we proceed by presenting the DL architecture that was used for predicting the parking violations. Finally, we present the proposed smoothing mechanism that can reduce the effect of annotation sparsity and noise.

3.1. Input Features and Ground Truth

As described before, parking slots in public on-street parking systems are divided into sectors. These sectors consist the fundamental block for which we predict the rate of parking violations. Given that the location and capacity of each sector are known, we can directly use the parking violation predictions for each sector in order to guide drivers towards sectors where parking slots will be most probably available. The first challenge we faced was to represent the geographical place of a sector in a way that would allow DL models to generalize. To this end, we avoided directly using a global coordinate system and we opted for indirectly encoding sector information using distances from several Points of Interest (PoI). A PoI is often visited by citizens on a frequent basis and, as a result, it is crowded most hours of the day. A PoI could be a sight, a central park, a museum, the city hall, and others. Given that traffic and demand for parking slots are higher across different PoIs, this way of encoding the information can allow a DL model to associate PoIs with expected parking violation rates, as well as encode sectors using distances from these points. To this end, we measured the distance between the center of each sector and the selected PoIs and used this vector to represent each sector. The way this information was encoded is shown in Fig. 1, where blue circles represent the PoIs and the red circle shows an example of a sector. A total of 19 points of interest were employed, leading to a 19-dimensional representation for each sector, denoted by $\mathbf{x}_s$. The capacity (number of available parking slots) of each sector was also included as a feature, denoted by x_c, since capacity can be related to the expected violation rate (e.g,. violation rate can be lower in larger sectors).

Furthermore, to enable the DL model to encode trends and identify periodic patterns regarding the expected parking violations we also included information regarding the current weekday (Monday to Sunday), day (1 to 31), and month (January to December). To better capture the periodic nature of these features and prevent discontinuities in the features we opted for using sine-based encoding for all of these features. For example, the weekday, denoted by x_w was encoded as:

$$x_w = \sin\left(2\pi\frac{w}{7}\right), \tag{1}$$

where w denotes the current day using sequential integer encoding, i.e., 0 for Monday, 1 for Tuesday, etc. Similarly, we extracted a feature for the current day x_d as:

$$x_d = \sin\left(2\pi\frac{d-1}{N_d}\right), \tag{2}$$

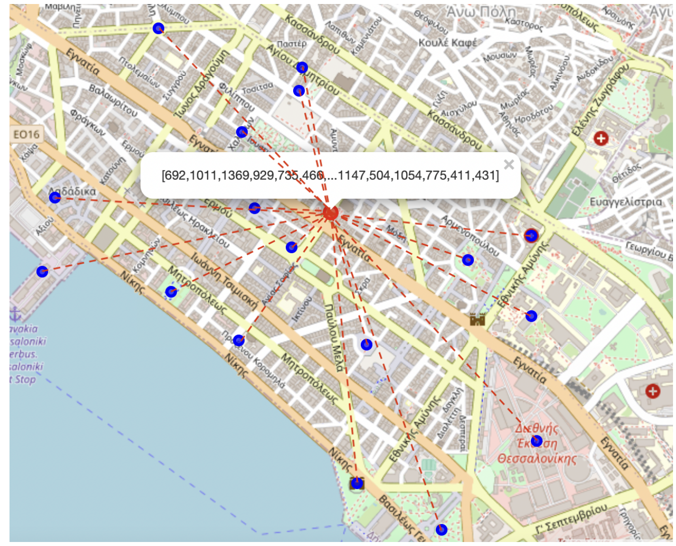

Fig. 1. Capturing the geographical location of a sector

where d is the current day (from 1 to 31) and N_d is the number of days for the current month. Moreover, the month feature x_m was calculated as:

$$x_m = \sin\left(2\pi\frac{m-1}{12}\right), \tag{3}$$

where m is the current month (ranging from 1 to 12). As we explain later in this section, the prediction horizon is one-hour. Therefore, each day was also divided into time slots (each with a one-hour duration) and this information was also included in the extracted features. Note that time slots do not span the whole day, since parking control is enforced from 7:00 until 19:00. Therefore, we did not use sine encoding for these features and we directly imprinted the temporal location of each time slot as its distance from the time when parking control is enforced.

Weather conditions also often affect traffic and demand for parking spaces, since bad weather can increase car use. Therefore, we used the hourly values of temperature and humidity as weather indicators. Temperature is represented in Celsius degrees, while humidity is provided as a percentage of the maximum possible humidity. Given that weather features usually do not immediately affect the behavior of drivers, i.e., if the temperature rises, traffic is not immediately affected, we opted for encoding weather features as the average of windows. To this end, the current temperature feature x_T for a time step t was calculated as:

$$x_T = \frac{1}{W}\sum_{i=1}^{W} T_{t-i}, \tag{4}$$

where T_t represents the temperature at the t-th time step and W denotes the window size used for the averaging. Note that we omitted the time step index t from the feature notation to reduce clutter. In this work, we used the current and 5 previous temperature measurements, i.e., $W = 6$. Humidity features x_h were similarly calculated.

Finally, two additional features were employed to enrich the information that is available to the DL model. The first one is a

Table 1. Input features used for parking violation rate prediction

Feature	Notation	# dims.
Sector distances to PoI	$\mathbf{x}_s$	19
Sector capacity	x_c	1
Time (weekday, day, month, time slot)	$[x_w, x_d, x_m, x_s]$	4
Weather (temperature, humidity)	$[x_T, x_h]$	2
Public holiday	x_v	1
Pandemic / COVID	x_f	1

binary variable, denoted by x_v, that is used to indicate whether the current day is a public holiday. Public holidays can affect traffic patterns and significantly alter the number of violation rates. We have also observed that during the recent COVID-19 pandemic traffic patterns were altered. Therefore, we also included an additional binary feature, denoted by x_f, to indicate whether the time slot belongs to a period of a pandemic or not. To avoid crowding and avoid the risk of infection, citizens turn down public transportation and prefer to use their own vehicles. As a consequence, traffic increases, which in turn also affects the incidence of parking violations. Even though we used this feature to only mark time slots that belong to the COVID-19 pandemic, we suspect that this feature might be also useful during subsequent flu seasons due to increased public awareness.

Table 1 summarizes the used features. All features were normalized using standardization, i.e., subtracting their mean and dividing by the standard deviation. The training set statistics were used for the normalization process. Also, the proposed prediction system operates on one-hour time slots aiming to predict the parking violation rate for each time slot and sector. The parking violation rate is calculated as:

$$y_s = \frac{N_s}{N_c}, \tag{5}$$

where p denotes the target violation rate to be predicted, N_s is the number of illegally parked cars and N_c is the capacity of the specific sector at a specific time slot (again we omit the sector and time slot indices to avoid cluttering the used notation). The number of illegally parked cars is calculated from police scan data. During such scans, a police officer scans cars' license plates that are parked in a sector. The scanner then checks if the parking fee has been paid (or if the car can legally park there without paying a fee) for each parked car. Then, this information is used to calculate the number of illegally parked cars within each sector and time slot. Then, each scan can be assigned to the time slot that is nearest to the center of each time slot.

3.2. Model architecture

In this work, we employed a residual DL architecture for predicting the parking violation rate in different sectors. The employed architecture is composed of six hidden layers and one output layer, as shown in Fig. 2. After conducting several experiments for selecting the most appropriate architecture, we designed a model that first projects the data into a higher dimensional space (512 dimensions) and then gradually reduces the dimensionality of the extracted representations in order to keep only the most relevant information for the task at hand. Indeed, after the first layer, which is equipped with 512 neurons, the number of neurons is gradually reduced by 2, i.e., the second layer has 256 neurons, the third one 128 neurons, and the fourth one 64 neurons. The fourth layer is used as a bottleneck layer before projecting the data back to 128 dimensions and employing a residual connecting from the third layer. Using this residual bottleneck block allows for improving the prediction accuracy over architectures that do not use residual connections. Finally, two layers with 32 and 1 neuron(s) respectively are used to regress the parking violation rate. The ReLU activation function was used for all the hidden layer (Glorot et al., 2011a). Note that further increasing the size of the employed architecture is not expected to lead to further accuracy improvements. The last layer employs a sigmoid activation function since it is used to predict the parking violation rate, which is always bounded between 0 and 1. To avoid pushing the sigmoid function to its extremes, we re-normalized targets between 0.1 and 0.9.

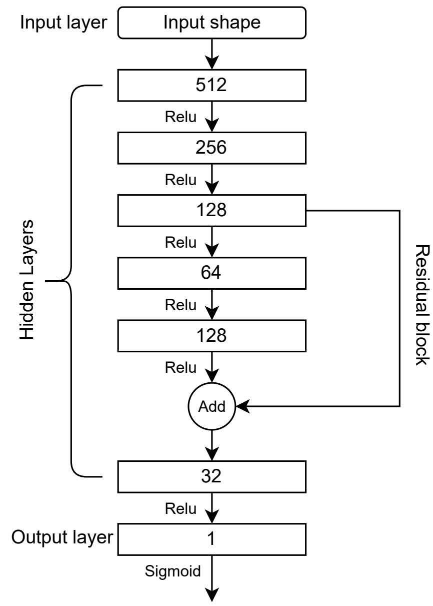

Fig. 2. DL model architecture used for predicting parking violation rate

Furthermore, the weights of the model were initialized using He uniform initialization (He et al., 2015), apart from the output layer, where Glorot uniform initialization was used (Glorot et al., 2011b). All biases were initialized to zero, while the output layer bias was initialized according to the average parking violation rate. The Adamax optimization algorithm was used for training the model (Llugsi et al., 2021). The mean squared error was used as the loss function. Finally, the learning rate was initialized at 0.001 and an exponential learning rate decay strategy with a decay rate equal to 0.25 was used for performing learning rate scheduling (Chollet et al., 2015).

3.3. *Target Smoothing and Data Augmentation*

Even though a large number of scans exist, the ground truth data remain sparse. For example, scans may concern only a specific sector and no information might be available for neighboring sectors at the same time. Furthermore, scans might span more than one time slot, often leaving the first and last time slots with very few scans, providing false information regarding the ground truth parking violation rate. To overcome this problem, we propose to distribute each scan to time slots assuming that the violation rate follows a smooth curve. This can mitigate annotation sparsity and discontinuity issues, improving the performance of DL models, as also shown in Section 4.

To this end, we applied a Gaussian-based smoothing scheme. After calculating the violation rate for each scanning session, we distributed the observed violation rate to nearby time slots using the following equation:

$$y = \frac{1}{|\mathcal{S}|} \sum_{s \in \mathcal{S}} \exp\left(\frac{-d_s}{\sigma}\right) y_s, \tag{6}$$

where s denotes a scanning session, $\mathcal{S}$ consists of scanning sessions overlapping or being nearby (by a difference of one time slot) to the current time slot, d_s is the distance in minutes of scanning session s from the current time slot's center, y_s is the violation rate calculated for scanning session s and $|\mathcal{S}|$ denotes the cardinality of set $\mathcal{S}$, i.e., the number of scanning sessions that can be assigned to the current time slot. The parameter σ controls the distribution process, i.e., a larger value distributes the violations to the nearby time slots, while smaller values allow for more steep changes in the parking violation rate between slots. A value of $d = 210$ minutes was used for the models developed in this paper. For example, if we observe a ratio of thirty five percentage (35%) of parking violations in a sector at twelve and fifty (12:50), i.e., in "12:00-13:00" time slot, then we can also assume that this ratio should be also partially assigned to the next time slot of "13:00-14:00", as shown in Fig. 3. As described before, this allows for filling potential gaps in the data, reducing the impact of sparse annotations and missing scans.

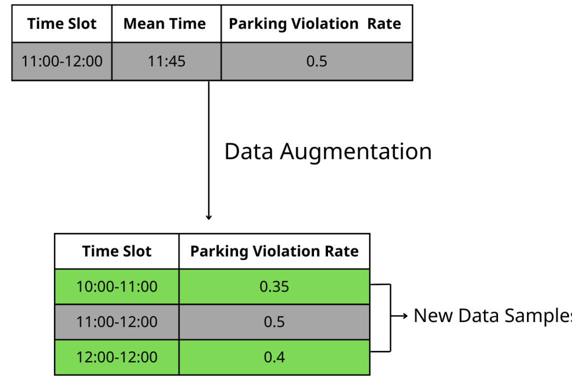

Fig. 3. The proposed data augmentation and smoothing method allow for assigning observed violation rates into nearby time slots, reducing the impact of sparse annotations and missing data scans.

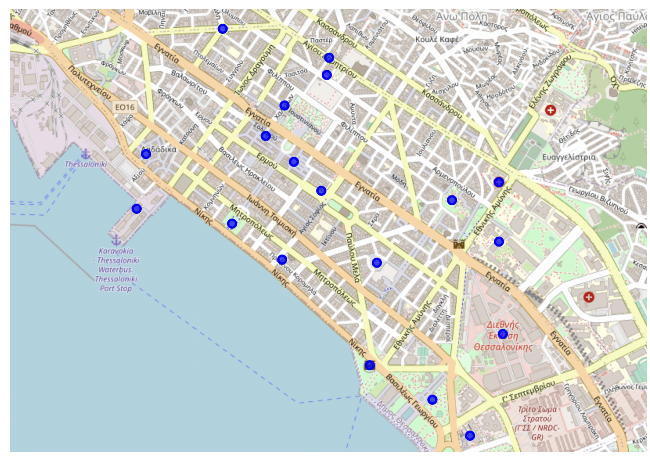

Fig. 4. A total of 19 PoIs were defined and used for representing various sectors of the used on-street parking system.

4. Experiments

In this section, we provide the experimental evaluation of the proposed method. First, we briefly introduce the collected data, information regarding the on-street parking system used, as well as the feature extraction methodology. Then, we proceed by presenting the experimental evaluation, including evaluating the effect of the proposed data smoothing and augmentation approach, as well as information regarding the impact of various design choices on the training of models.

4.1. *Evaluation Setup and Data*

For all the conducted experiments, we used data collected from Thessaloniki's on-street public parking system called THESi[1]. THESi consists of about 4,700 parking slots in the city's center, which are distributed into 396 separate sectors. The aim of the proposed method is to predict the parking violation rate for each of these sectors. We used historical data that consist of scans conducted by the city's traffic police, as well as weather data from OpenWeather[2]. A total of 3.8 million scans that were captured through 300,000 checks were used in the conducted evaluation. Furthermore, we manually defined 19 PoIs used for encoding the distances for each sector, as described in Section 3. The selected PoIs are shown in Fig. 4. The proposed method was implemented using the keras framework (Chollet et al., 2015) (v2.6) and Python v3.8. Regarding the management of the spatial information we used the library geopy[3] (v2.2). The code used for the conducted experiments is publicly available at `https://github.com/nikgeokar/Parking_Violation_Prediction`.

We provide a brief data analysis before using the collected data for predicting parking violations. The mean parking viola-

[1]https://thesi.gr

[2]https://openweathermap.org

[3]https://pypi.org/project/geopy/

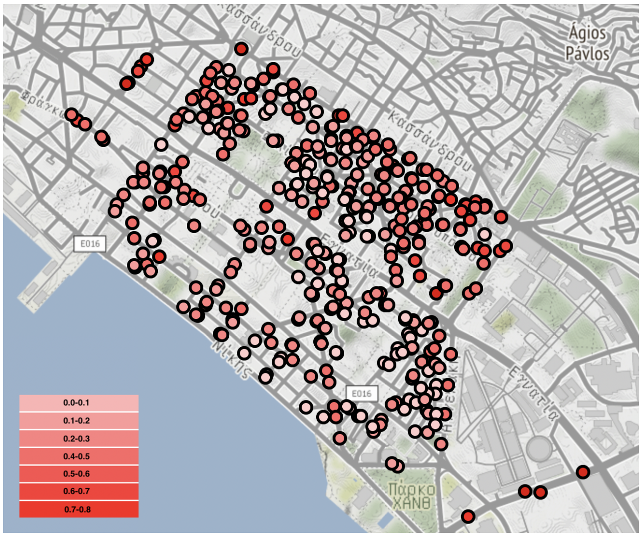

Fig. 5. Spatial distribution of parking violations. Darker values indicate a higher average parking violation rate per sector.

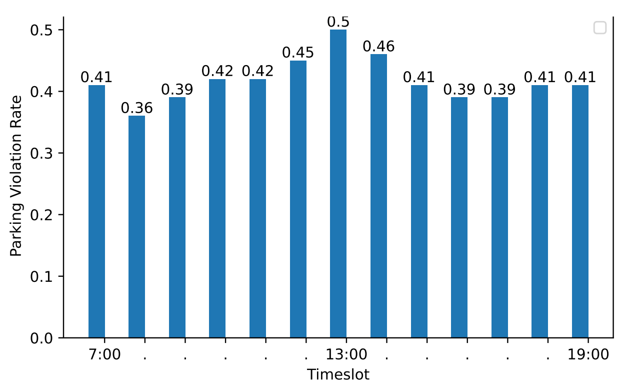

Fig. 6. Average parking violation per time slot

Table 2. Comparing statistics before and during COVID-19 pandemic

Metric	Before COVID-19	During COVID-19
Mean	0.39	0.46
Median	0.33	0.43

tion rate is 0.41 ± 0.28, while the parking violation rate ranges between zero (0) and one (1). Given that an average sector has eleven parking slots, this parking violation rate means that three to four (3-4) parking slots are expected to be illegally occupied. We also examined the spatial distribution of parking violations in Fig. 5, where darker colors indicate a higher parking violation rate. The higher mean parking violation of a sector is 0.78, while the lower is 0.1. We observe a higher parking violation rate in the upper region of the city. Another observation is that parking violations are higher in remote sectors. This can be probably explained since drivers might believe that these sectors are not as frequently scanned for illegal parking.

We also examined how the parking violation rate varies within a day. The statistics are provided in Fig. 6, where the average parking violation rate per hour is reported. Note that

Table 3. Parking violation rate prediction evaluation (the mean absolute error is reported).

Method	Raw Test Set		Smoothed Test Set	
	MAE	MSE	MAE	MSE
Without Smoothing	0.175	0.0515	0.173	0.0509
With Smoothing	**0.169**	**0.0497**	**0.146**	**0.0429**

parking control is enforced from 7:00 until 19:00. Therefore, data only contains scans within this period. Note that mid-day (13:00-14:00) has the highest parking violation rate. Another important piece of information for understanding the structure of the data is the percentage of sector spaces that are scanned at each check. This percentage can be easily obtained by dividing the number of scans by the number of spaces in the sector. On average, about 76% of sector spaces are scanned in each check. Furthermore, we also evaluated whether the COVID-19 pandemic had any impact on the average parking violation rate. The results are reported in Table 2, where we compared the period before and after the onset of the pandemic. Indeed, parking violations seem to increase during the pandemic due to increased car use.

Finally, the effect of the proposed data smoothing approach on the distribution of parking violations is shown in Figs. 7 and 8. Using the proposed method leads to a significantly smoother distribution with fewer discontinuities that were probably caused by missing data points / lack of enough scans. At the same time, the proposed method allowed us to more than triple the size of the data available to train the model.

4.2. Experimental Evaluation

For all the conducted experiments, we used 80% of the data to train the model, while the remaining 20% was used to test the model. The mean absolute error (MAE) and the root mean square error (MSE) were used as the evaluation metrics. First, we have conducted experiments to evaluate the impact of the proposed temporal smoothing method which assigns the existing ground truth annotations to time slots. The evaluation results are reported in Table 3. The baseline model without any smoothing achieves a MAE of 0.175, which demonstrates that we can accurately predict the parking violation rate using the proposed method, since the MAE of a baseline average value predictor (using the average violation rate as the prediction) is 0.251. Furthermore, using the proposed data augmentation and smoothing method for the train set allowed for further reducing the error to 0.169 on the original test set, while the error dropped to 0.146 when the data smoothing methodology was applied to the whole dataset. These results demonstrated the importance of employing the proposed data augmentation and smoothing approach to fill missing data and reduce data discontinuities. Similar results are also observed for the MSE metric.

Furthermore, we have conducted an ablation study to evaluate the impact of using each of the proposed features. The results of this study are provided in Table 4. Again, both MAE and MSE are reported. Each feature seems to indeed contribute to increasing the accuracy of the system. Time features, followed by weather features, seem to lead to the most significant

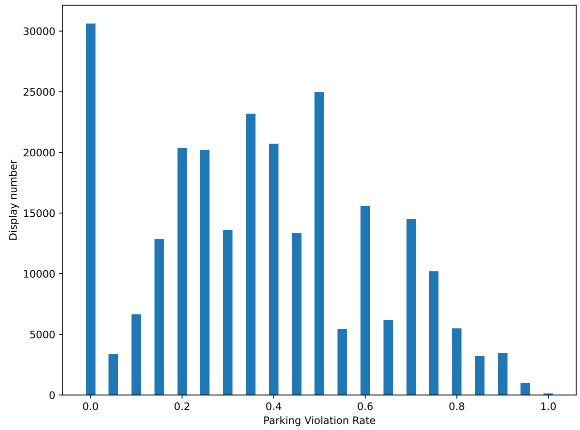

Fig. 7. Distribution of parking violation rate (raw values)

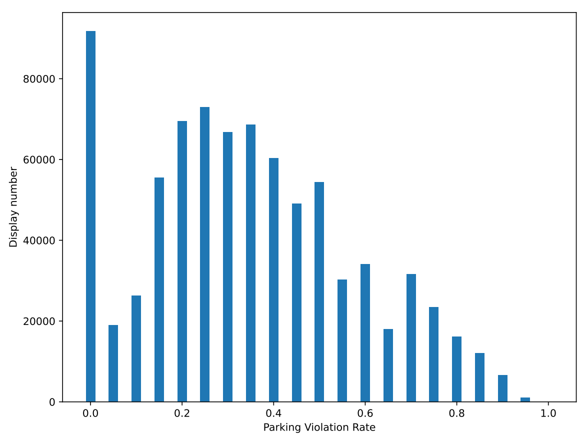

Fig. 8. Distribution of parking violation rate (after data augmentation and smoothing)

increase in the accuracy of the model. On the other hand, holiday indication features seem the least important, probably due to this information being already partially encoded to time features. We have also conducted a statistical significance test to evaluate whether there are statistical significant differences between using different sets of features. More specifically, we used a t-test to compare between using the first two features (sector distance to PoI and sector capacity) to the possible combinations of the remaining ones. The differences were statistically significant for both MAE (p-value = 0.002) and MSE (p-value = 0.0009).

Furthermore, we have conducted 4-fold cross-validation experiments, where we monitored the validation MAE and MSE during the training epochs, to select the most appropriate number of training epochs for each of the two evaluation setups (with and without smoothing) to ensure a fair comparison between them. The results are provided in Fig. 9. Note that using the smoothed training set leads to significant improvements over directly using the raw training set. We also plotted the MAE/MSE for the smoothed validation set, where again we observe that the training process converges smoothly, while achieving significantly better MAE, confirming the results reported in Table 3.

Table 4. Ablation study: Evaluating the impact of each feature on the parking violation rate prediction error (MAE and MSE). The improvement (percentage reduction in MAE/MSE) over the previous line/feature combination is also reported in parentheses.

Features: Sector distances to PoI	Sector Capacity	Time	Weather	Holiday	Pandemic	MAE	MSE
✓						0.211	0.062
✓	✓					0.206 (2.4%)	0.061 (1.6%)
✓	✓	✓				0.185 (10.2%)	0.054 (11.5%)
✓	✓	✓	✓			0.176 (4.9%)	0.052 (3.7%)
✓	✓	✓	✓	✓		0.173 (1.7%)	0.051 (2.0%)
✓	✓	✓	✓	✓	✓	0.169 (2.3%)	0.050 2.0%)

Table 5. Experimental comparison of the proposed method to Gao et al. (2019). Results are reported on the raw test set.

Method	MAE	MSE
Gao et al. (2019)	0.191	0.0561
Proposed	**0.169**	**0.0497**

Finally, in Table 5 we compare the proposed method to Gao et al. (2019). To this end, we have used the features proposed in Gao et al. (2019) with the same architecture and prediction targets used by the employed dataset in order to allow for a fair comparison between the two approaches. The results indicate that the proposed method leads to significant improvements both with respect to MAE and MSE (relative improvement of over 10% for both cases).

5. Conclusions

In this work, we presented and evaluated a DL-based model for on-street parking violation prediction. Several challenges were faced during the development of such a system, ranging from data sparsity challenges to encoding data in the most appropriate format for the employed DL model. To address these issues, we developed a novel approach that assigns the existing ground truth annotations to time slots, leading to significant performance improvements. Other challenges include imprinting input data, such as the geographical location of each sector, time, and other information, such as pandemic measures (i.e., due to COVID-19) in an efficient manner. We evaluated the proposed method using novel data from the THESi system implemented in Thessaloniki, Greece, while we also presented various aspects of the employed data to provide more insight

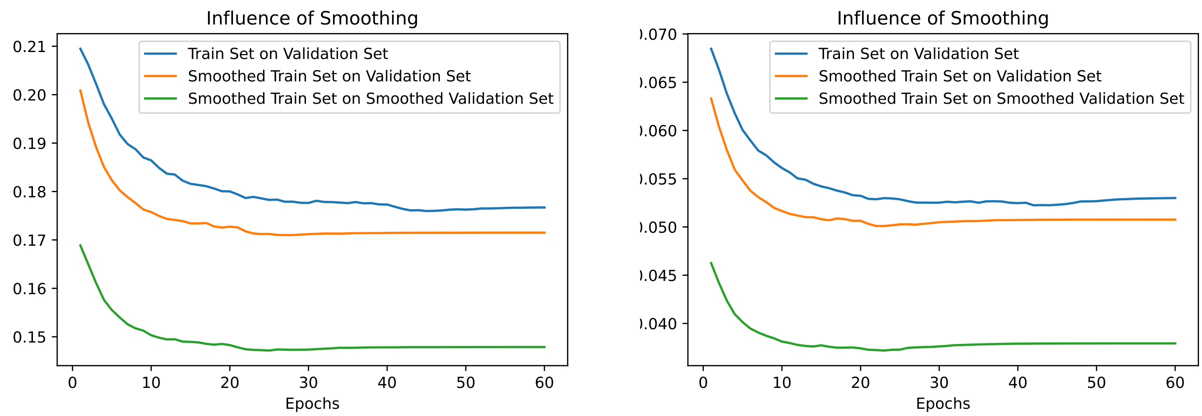

Fig. 9. Validation error during training for the two setups used (with and without smoothing). MAE is reported in the left figure and MSE is reported on the right figure.

into this especially challenging problem. The obtained results indicate that we can perform fine-grained on-street parking violation prediction using indirect features (e.g., temperature, time, distance to PoIs, etc.), enabling the integration of DL-based approaches to on-street parking systems for improving their performance with minimal effort and cost. At the same time, we have demonstrated that using appropriate data augmentation approaches can improve prediction accuracy, minimizing the impact of missing data. Even though this was only applied on a temporal level, it paves the way for its potential use at a temporal level. This could also enable other features for which missing values might occur frequently, such as traffic information, to be included in the training and deployment pipeline further improving the prediction accuracy.

There are several interesting future research directions. First, the current model can only indirectly model the spatial relationships between sectors. To overcome this limitation, graph neural networks could be employed for better modeling of the spatial relations between sectors (Wu et al., 2020; Manessi and Rozza, 2021). Furthermore, traffic on city streets can affect the rate of parking violations, hinting that this could be an additional feature that can be included to further improve the performance of the presented model. Furthermore, even though city traffic information can be a valuable predictor, this information typically is not available for all sectors/roads, requiring the use of methodologies that can work even under the presence of partial information.

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