Computing and Informatics, Vol. 44, 2025, 661–681, doi: 10.31577/cai_2025_3_661

MACHINE LEARNING APPROACH FOR ECOLOGICAL PUBLIC TRANSPORT SYSTEMS

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Abstract. Using convolutional neural networks and genetic programming, this study presents a new composite technique for modeling bicycle traffic in the town of Novo mesto, Slovenia. Every town needs public passenger transportation because the current transportation system has well-known issues like congestion, environmental effect, a lack of parking spaces, increased safety hazards, and excessive energy consumption. Urban transport is crucial for the functionality of any city. High-quality and usable urban transport not only affects the functionality of the city as an economic and social center, but it also reduces the number of passenger cars on the streets. The Novo mesto region, which has a population of around 30 000 people, is a major industrial center that is strongly reliant on metropolitan transportation. Unfortunately, the urban traffic of Novo mesto still has a relatively weak influence on the transport connectivity of the wider area. The study's goal is to examine and simulate bicycle rentals. For 35 weeks, convolutional neural networks and genetic programming were utilized to anticipate bicycle traffic. Three types of models were applied to study the impact of weather conditions on bicycle traffic: linear regression, genetic programming, and feed-forward neural networks. The proposed approach will be useful for cities with similar needs around the world.

Keywords: Machine learning, genetic programming, convolutional neural networks, multiple regression, bicycle traffic, public transport

1 INTRODUCTION

Public transport (local public transport) [1] is the transport of people by bus, tram, commuter train, train and other motor vehicle, or by renting a bicycle in regular traffic. Thus, urban public transport is one of the mechanisms that guarantees citizens their constitutional right to work, education, healthcare, and recreation. In addition, the PPT industry itself is a source of jobs. With the growing urban population and increasing daily traffic, the development of more sustainable urban transport systems is crucial in many cities around the world. Increasingly, public transport and cycling are being promoted to reduce traffic problems such as congestion, pollution, expensive road infrastructure, accidents, and congestion. The benefits of cycling for the community are mainly related to the quality of life, the quality of the environment, and the long-term savings from car use [2]. A major environmental problem of the Municipality of Novo mesto is air pollution with PM10 particles, which is a consequence of the basin location with unfavorable winter climatic conditions in which the loads increase due to small obsolete biomass fireplaces and traffic. Although the measured average annual concentration limit of PM10 particles in the air in Novo mesto has have been exceeded since the beginning of measurements in 2010. Every year (except 2014) we detect an exceeded number of days (35) per year with an exceeded daily concentration limit [3]. Due to the overruns, the entire area of the city municipality was declared as degraded. The government has adopted its Air Quality Plan, which includes a program of measures aimed at improving air quality. This program focuses on various strategies related to traffic and mobility management. The chemical composition of emissions is influenced by factors such as the type and quality of fuel used, the production technology, the combustion process in the engine, and the engine's overall condition. At present, many countries are focusing on green technologies in industry, construction, agriculture, and production of environmentally friendly materials, fundamentally new services aimed at improving the quality of life [4, 5]. The world is beginning to actively introduce and develop new products that have a positive influence on human living conditions, the environment, and national and regional environmental policies. Factors that affect the extent of transport have an impact on the environment. The strong source of environmental pollution in cities is traffic and its marks are constantly increasing. Several factors impact the level of pollution: intensity, speed, and the composition of traffic flow; the types of engines; the type and quality of road surfaces; planning decisions of areas; the presence of green spaces. The main idea of sustainable development is to satisfy modern consumer needs in such a way that future generations will be able to satisfy their needs. Planet Earth can be considered a closed system. If something arrives in one place, it disappears in another. The only incoming stream from outside this system is solar energy. Environmental pollution from stationary sources in transport comes from industries that repair vehicles, auxiliary industries, buildings, and structures.

It is known that effective and "smart" public transport can only be organized by collecting individualized detailed data on its users. This data should be complemented by additional information, such as camera recordings on major roads and intersections, data on the use of other systems, data on weather and unusual phenomena [6]. A practical step towards achieving this has been the use of data from smart cards [7, 8, 9], which must be supplemented by the information regarding the location of all traffic participants [10]. In larger cities, the amount of such data can be very large, so we encounter the need for software and hardware suitable for big data [11] which requires the use of supercomputers. New concepts of mobility (co-ownership, co-ownership of means of transport) are on the rise and are working great in many cities. However, most of these solutions are only implemented in large cities, and cities with up to 100 000 inhabitants are generally too small to implement business models, i.e. sharing economies [12] behind these systems. This indicates that private providers, due to their business interests, either do not offer solutions or may be unaware of existing ones that could benefit municipalities. This situation can be frustrating on the one hand; however, it also presents an opportunity for innovative municipalities and regional development agencies to take the initiative.

This work is motivated by a desire to increase the number of bikes in the GoNM system, thereby reducing car use. This was measured through the number of uses of bicycles in the GoNM system throughout the year. By doing so, we can reduce emissions and simultaneously improve public health. The bike-sharing system is affected by the weather. As a result, one of this research's unanswered questions is how many bikes will be shared in different weather circumstances. The challenge can be broadened by incorporating more public transit systems that would revolutionize the entire city's transportation and make the city even smarter. The solution to this problem is based on artificial intelligence methods.

Artificial neural networks [13] are widely used to solve various real-world classification and prediction tasks. Problems such as speech recognition and image processing tasks are solved with high accuracy today. A convolutional neural network (with the acronyms CNN or ConvNets) [14] is a special case of deep learning neural networks. It uses single or multiple convolutional layers that usually perform a 2D convolution since the inputs to a CNN are usually images. In recent years CNNs have become very popular with impressive results in the area of computer vision. Today, deep learning is at the heart of many companies' services: Facebook uses neural networks for auto-tagging algorithms, Google searches for user photos, Amazon generates product recommendations, Pinterest personalizes a user's home page and Instagram refines its search infrastructure. But the classic and most popular use case for CNNs is image processing.

Cellular automata (CA) have been extensively studied since the 1960s and were originally designed and studied to create artificial evolution from self-replication presented by John von Neumann [15]. Genetic Programming (GP) [16] is a problem-solving technique that combines evolutionary and computer programming ideas. The GP algorithm [17] works according to the following principles. Hybrid evolutionary computation [18] is a general, adaptable, robust, and versatile method to solve challenging global optimization problems which can also be used to solve real-world situations. The purpose of this research study is to offer a model of bicycle traffic with meteorological conditions that incorporate CNNs, multiple regression, GP, and a new approach of combining CNNs and GP.

The rest of the paper is structured as follows: Section 2 explores related work on the topic, while Section 3 outlines the study methods used. The first is a demonstration of GoNM, a Slovenian automated bicycle rental system. Following that, data preparation is covered with subsections for cycling data and weather data. The third subsection discusses data preprocessing and modeling approaches. Section 4 presents the results of the analysis and discussion of the Convolutional Neural Network model of bicycle traffic, the impact of weather on bicycle traffic, the multiple regression model, the Genetic programming model, and the Composite model of Convolutional Neural Networks and Genetic programming. The paper concludes with a conclusion and recommendations for future research.

2 RELATED WORK

Weather conditions have a significant impact on the utilization of public bicycles. Cars, public transportation, and active transportation modes like walking and bicycling have all seen a modal shift as a result of bike-sharing schemes [19]. Bike-sharing as a mode of transportation may improve the quality of the urban environment [20] and increase physical well-being [21]. In [22] passengers' first/last mile mode choices before and after the installation of a bike-sharing system were studied and it was discovered that the majority of switched trips to bike-sharing were initial walking or private bicycle trips. Because bicycle traffic data (e.g. speed, bike volume) is difficult to obtain, academics and practitioners are forced to plan the deployment of bike-share systems (BSS) using models that do not account for observed bike quantities [23]. [24] showed that results indicate that weather conditions should always be taken into consideration when analyzing cycling, especially on the road safety analysis. Temperature, wetness, and whether it was a workday effect all that influenced the rental bike demand at different times [25]. Numerous studies have been conducted on traffic flow and public rental bike demand forecast, only a handful of them have focused on moment-based demand in public bike-sharing systems [26]. Other innovations emerged with the bike-sharing system including electric assist bikes, solar-powered stations, mobile stations, and the establishment of self-regulation policies through smartphone applications [27]. The study [28] presented a public bicycle system in the old urban region of Zhenhai in Ningbo city, the newly established prediction model for rental. Results show that the model can predict the daily rental demand, rental demand during the morning peak, returns during the morning peak, rental demands during the evening peak, and returns during the evening peak. The demand prediction model can provide a significant theoretical basis for preparing the layout stations, operation and management strategies, and vehicle scheduling in the public bicycle system. China is suffering from severe negative consequences of high private vehicle usage in big and densely populated cities. Nevertheless, a long history of bicycle usage in the country provides great potential for such a green form of travel to be part of public and private transportation. The findings show that bike-sharing systems have varying degrees of success. The configurations which seem the most sustainable consider and integrate elements relating to transport planning, system design, and choice of business model [28].

3 METHODOLOGY

3.1 Automatic Bicycle Rental System in the Town of Novo Mesto

Public urban passenger transport has been established in the town of Novo mesto, Slovenia. In 2017, the town acquired the GoNM automatic bike rental system. The elderly and the disabled have the option of free transport which operates voluntarily. There are also officially some taxi services in Novo mesto, but the number of vehicles is extremely small. Since 2017, the GoNM automatic bicycle rental system has been established in Novo mesto comprising 14 stations. A total of 70 bicycles are available of which 45 electric bicycles were added to the system in 2018. The user of the GoNM system can choose between the following options: the annual membership fee for users logging into the system is 25 EUR per calendar year; a monthly membership fee of 5 EUR is also available. The membership fee is valid for one calendar year. It is, therefore, necessary to develop a methodology to estimate and analyze the demand for bicycle rental. Figure 1 shows the geographical map of the 14 bike rental stations in Novo mesto.

3.2 Data Preparation

3.2.1 Bicycle Data

The municipality of Novo mesto provided bicycle rental data for 14 stations for 35 weeks between March 25, 2019, and November 25, 2019. The data is analyzed using Microsoft Excel software and pivot tables. The numbers of bike rentals for 14 stations for the 13$^{\text{th}}$ week are presented in Table 1.

Figure 2 shows the total number of bike rentals for the 35 weeks.

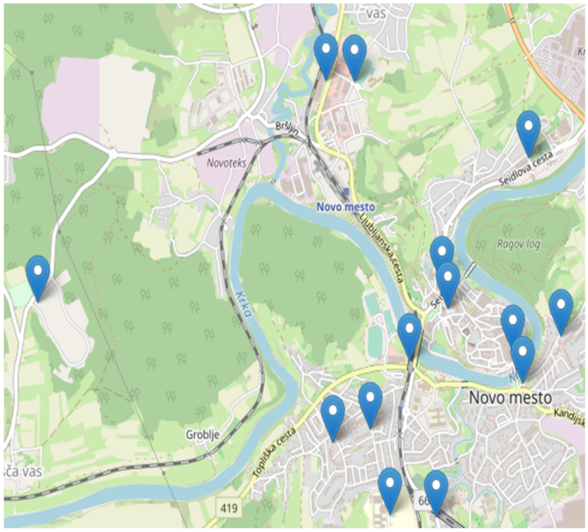

Figure 1. The geographical map of the 14 bike stations in Novo mesto, Slovenia

3.2.2 Weather Data

The Meteorological Society Zeus in Slovenia provided weather data for each day, including temperature (T), rainfall (R), wind speed (W), and relative humidity (H). The averages of all data were calculated for 35 weeks. Figure 10 shows the weather information: average temperature [C], average rainfall [mm], average wind speed [m/s], and average relative humidity [%].

S	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	3	4	3	0	3	2	0	1	2	1	2	5	0	3
2	3	1	2	8	2	2	0	5	4	0	0	1	1	1
3	4	1	4	0	3	1	7	2	0	0	1	3	0	0
4	3	6	1	5	3	0	2	1	3	1	0	2	2	4
5	1	3	7	1	13	13	0	3	1	1	1	11	0	1
6	1	2	2	0	14	7	3	2	3	0	1	5	1	2
7	0	0	6	3	1	3	4	0	0	0	1	0	0	0
8	5	2	1	4	2	0	0	8	3	1	0	3	5	3
9	1	1	0	5	0	1	1	3	7	1	0	2	0	3
10	1	1	0	1	2	1	0	0	1	2	0	0	0	0
11	2	0	1	0	0	2	0	0	1	0	26	0	1	0
12	10	2	4	1	10	2	0	1	3	1	0	11	0	0
13	0	1	1	1	0	2	0	6	0	0	0	0	5	4
14	6	0	0	0	2	3	3	1	3	0	0	1	5	4

Table 1. Numbers of bike rentals for 14 stations for the 13^{th} week

Figure 2. Number of bike rentals for 35 weeks

3.3 Data Preprocessing

Most of the bicycle traffic models we have discussed are based on statistical analysis techniques, such as linear regression and correlation analysis. To achieve accurate predictions, many authors incorporate artificial intelligence methods. In this study, a method using convolutional neural networks, multiple regression, and genetic programming to model bicycle traffic is presented. Moreover, a new composite model with convolutional neural networks and genetic programming is proposed.

Originally, the idea was to use cellular automata (CA) [29] to model the dynamical system of bicycle rentals. In cellular automata, the next state of each cell is determined by the state of the cell's neighbourhood including the cell itself. Cellular automata may be one, two, or three-dimensional (1D, 2D, 3D). However, since the values are ordered rather than categorical, it is more convenient to use a slightly different but more powerful model: the Convolutional Neural Network (CNN). This model employs multiple kernels that function as filters, which are then combined, typically using a fully-connected feedforward neural network. Since bike stations are not arranged like on a chessboard, they have been mapped into a 1D space, allowing us to define a convenient neighbourhood. So, first, the Sammon's mapping [30] was applied to map the locations of the bike stations from 2D to 1D space, while preserving topology as closely as possible. This means that a pair of points that are close to each other in the original space must also be close in the projected space. The Sammon's mapping searches for the distance matrix $[d_{ij}]$ in the second (lower-dimensional) space, minimizing the following cost function:

$$E = \frac{1}{\sum_{i<j}^{N} d_{ij}^{*}} \sum_{i<j}^{N} \frac{(d_{ij}^{*} - d_{ij})^2}{d_{ij}^{*}}, \tag{1}$$

where $[d_{ij}^{*}]$ is the distance matrix in the original (two-dimensional) space. There exist various heuristic search methods to seek the optimal solutions, but for our purpose, a simple comprehensive search was used, since the number of bike stations was only 14. Every possible permutation was tried and evaluated. The optimal solution is depicted in Figure 3.

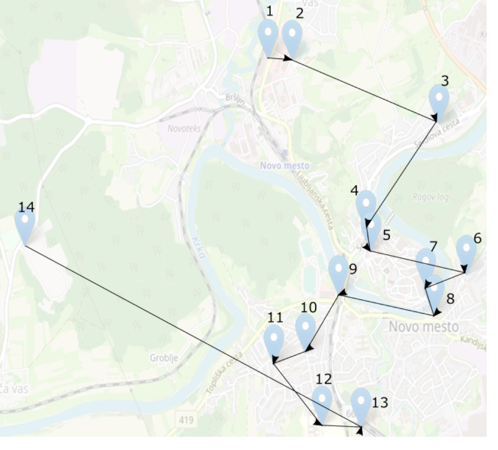

Figure 3. The optimal 1D map, preserving topology as close as possible for Figure 1

The input to the model was a $n \times n$ matrix B, consisting of the bike traffic between pairs of stations, such that the element B_{ij} tells how many bicycles were borrowed at station i and returned to station j in a given week, as shown in Figure 4. Since the ordering of bike stations is defined by a topology-preserving mapping, we expect that neighbouring values of bike rentals in this matrix may affect each other. Two examples of neighbourhoods can be seen in Figure 4. The idea was to predict the central value of such neighbourhoods at the next discrete time (i.e., week) by the values of all cells in the neighbourhood.

3.4 Modeling

3.4.1 Convolutional Neural Network Model of Bicycle Traffic

Two examples of cells with their neighbourhood are shown in matrix B: one sized 3×3 around cell B34 with a value of 5 (bicycles) and the other sized 5×5 around

$$B = \begin{bmatrix} 10 & 2 & 2 & 3 & 3 & 3 & 3 & 0 & 0 & 0 & 6 & 0 & 0 & 2 \\ 0 & 3 & 0 & 0 & 1 & 3 & 4 & 2 & 0 & 0 & 5 & 0 & 0 & 1 \\ 0 & 0 & 1 & 5 & 0 & 0 & 0 & 2 & 3 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & \boxed{5} & 5 & 2 & 3 & 7 & 3 & 5 & 0 & 0 & 3 & 0 & 2 \\ 0 & 1 & 1 & 1 & 3 & 3 & 12 & 9 & 2 & 0 & 4 & 2 & 0 & 0 \\ 3 & 4 & 0 & 3 & 3 & 4 & 12 & 4 & 5 & 0 & 0 & 5 & 0 & 0 \\ 11 & 1 & 0 & 13 & 9 & 9 & 24 & 10 & 5 & 0 & 2 & 2 & 0 & 2 \\ 4 & 3 & 3 & 2 & 3 & 5 & 9 & 9 & 0 & 0 & 1 & 1 & 0 & 0 \\ 2 & 0 & 0 & 2 & 5 & 5 & 4 & 3 & \boxed{4} & 0 & 1 & 2 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 2 & 2 & 0 & 0 & 1 & 1 & 4 & 0 & 2 & 0 & 7 & 4 & 0 & 0 \\ 1 & 0 & 0 & 0 & 4 & 2 & 6 & 1 & 3 & 0 & 4 & 5 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 2 & 3 & 0 & 0 & 3 & 0 & 0 & 0 & 4 & 0 & 0 & 1 & 0 & 21 \end{bmatrix}$$

Figure 4. An example of matrix B with two types of neighbourhoods shown: 3×3 and 5×5

a cell with a value of 4. The number of bikes hired at station i and returned to station j is denoted by B_{ij}. The bikes returned to the same station are referred to by diagonal elements. We may assume that the value of a cell together with its neighbourhood can predict the value of this cell for the next week better than without the neighbourhood.

A Convolutional Neural Network (CNN) was used to learn the rules that can predict the next state of each cell, i.e. a bike station based on its current state and the state of its neighbourhood, an artificial neural network architecture capable of such mapping (Figure 5).

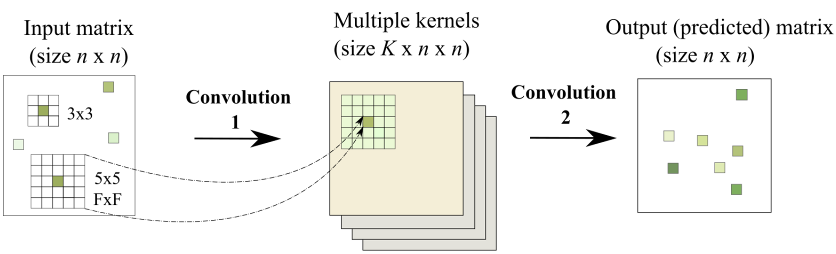

Figure 5. Illustration of the Convolutional Neural Network architecture

The input 'image' is matrix B, which is processed by two convolutional layers, and the state of the second layer is the predicted next state.

A 2D convolution computes a double sum over $F \times F$ neighbouring elements in an image or other 2D data structure. The filter size F can be 3 or 5, giving a filter size of 3×3 or 5×5, respectively. Since an additional bias term is added for greater flexibility, there are $F \times F + 1$ free parameters or weights. In the case of multiple kernels (K), each has its filter, so the number of weights in the second layer is $K(F^2+1)$: KF^2 weights h and K biases b. The 2D convolution is computed as

$$y_{k,ij} = \sum_{m=1}^{F}\sum_{n=1}^{F} x_{ij} \cdot h_{k,i-m,j-n} + b_{k,ij}, \tag{2}$$

for $k = 1, \ldots, K$. The activation function is the sigmoid $1/(1+\exp(-y_{k,ij}))$.

The output layer has, on the other hand, each kernel multiplied by its $F \times F$ weights (denoted by g) and a single bias:

$$z_{ij} = \sum_{k=1}^{K}\sum_{m=1}^{F}\sum_{n=1}^{F} y_{k,ij} \cdot g_{k,i-m,j-n} + b_{ij}, \tag{3}$$

giving the total number of weights in the output layer equal to $KF^2 + 1$. For example, if $F = 5$ and $K = 5$, then there are $5(25+1) = 130$ and $5 \cdot 25 + 1 = 126$ weights in both layers, respectively. The activation function is again the sigmoid.

3.4.2 Linear Regression

By fitting a linear equation to the observed data, multiple linear regression seeks to model the relationship between two or more explanatory variables and a response variable. Each value of the independent variable x has a corresponding value of the dependent variable y. Given n data, the model for multiple linear regression is

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i \quad \text{for } i = 1, 2, \ldots, n. \tag{4}$$

3.4.3 Genetic Programming

The main distinction between genetic programming (GP) and genetic algorithms (GA) is the representation technique. In genetic algorithms, individuals are represented by a series of integers, while in genetic programming, a computer program is represented by an individual. GP generates programs based on the principles of natural selection (evolution). We begin with a collection of hastily assembled programs that represent the initial population. Then, via crossover and selection (Figure 6) the next generation is acquired.

Table 2 shows the parameters of GP.

Finally, a newly developed composite system of modeling is presented. The model utilizes two methodologies that yielded optimal results. Consequently, the concept of a composite modeling system is designed to predict effects based on images of a matrix [31].

4 RESULTS ANALYSIS AND DISCUSSION

Figure 7 shows the traffic matrix B for each of the 35 weeks, shown as a grayscale image. Black dots indicate 20 or more bicycles transferred between two stations,

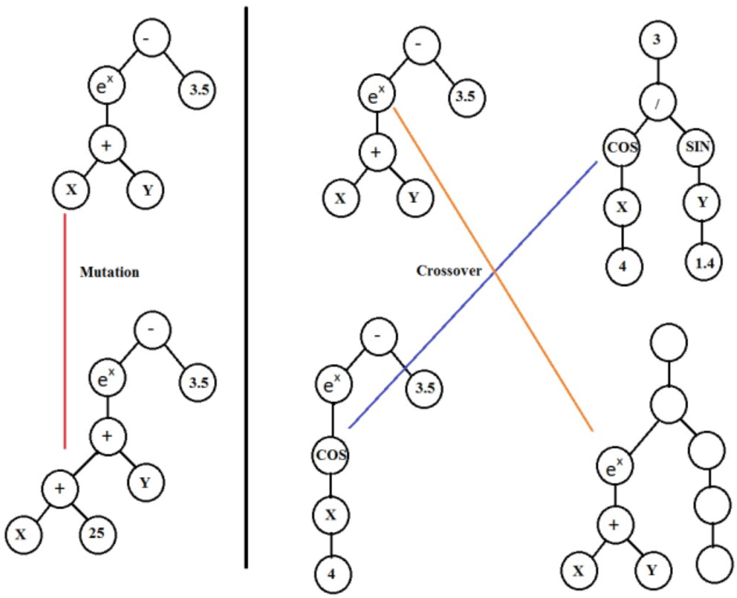

Figure 6. Genetic mutation and crossover

Parameter	Number
Size of the population of organisms	400
Maximum number of generations	100
Reproduction probability	0.3
Crossover probability	0.5
Maximum permissible depth in the creation of the population	7
Maximum permissible depth after the operation of crossover of two organisms	10
Smallest permissible depth of organisms in generating new organisms	2
Tournament size used for selection of organisms	6

Table 2. Parameters of genetic programming for the number of rentals

white dots indicate 0 bicycles, and gray dots any integer in between. Figure 8 shows the traffic matrix B predictions with the CNN. The meaning of the gray levels is the same as in Figure 7. Note also that the first week cannot be predicted.

To verify the utility of such a cellular model of the traffic dynamics, it must be checked whether the prediction with the CNN is better than a naive prediction, i.e., the one that predicts for the next week the actual value of the current week. Any useful prediction must be better than that baseline. The mean squared error (MSE) of the naive prediction was 3.50, while the MSE of the CNN was 2.36, meaning that the mean absolute error was 1.54. Figure 9 shows the actual and the data predicted by CNN.

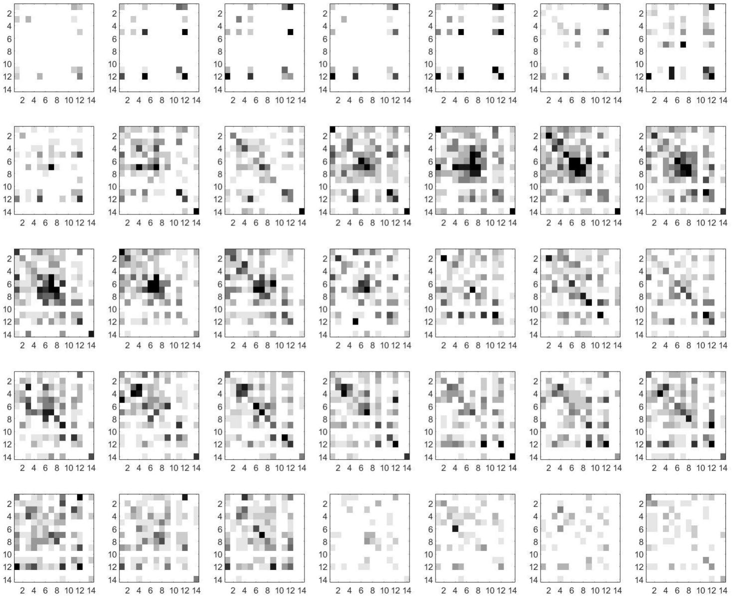

Figure 7. Traffic matrix B for each of 35 weeks, shown as a grayscale image. Black dots: 20 or more bicycles, white dots: 0 bicycles, gray: any integer in between

4.1 Impact of Weather on Bicycle Traffic

Bicycle rentals together with the weather data are displayed in Figure 10.

4.1.1 Multiple Linear Regression Model

The four weather variables (temperature, rainfall, wind, and humidity) served as the independent variables to predict the total number of weekly bicycle rentals by the multiple linear regression model. Table 3 shows the results. The value of R^2 is 0.571. As it seems, the only input variable with a p-value lower than 0.05 is the temperature which has its non-standardized coefficient β of 30, which means that on average with each degree of temperature the number of bicycle rides increases by 30. This model has the mean squared error (MSE) of 0.0346, which means that the mean absolute error (MAE) would be 0.19.

The multiple linear regression model of bike rentals is as follows:

$$\text{rentals} = 29.97 \cdot T + 15.32 \cdot R - 3.415 \cdot W + 0.1109 \cdot H - 89.06. \tag{5}$$

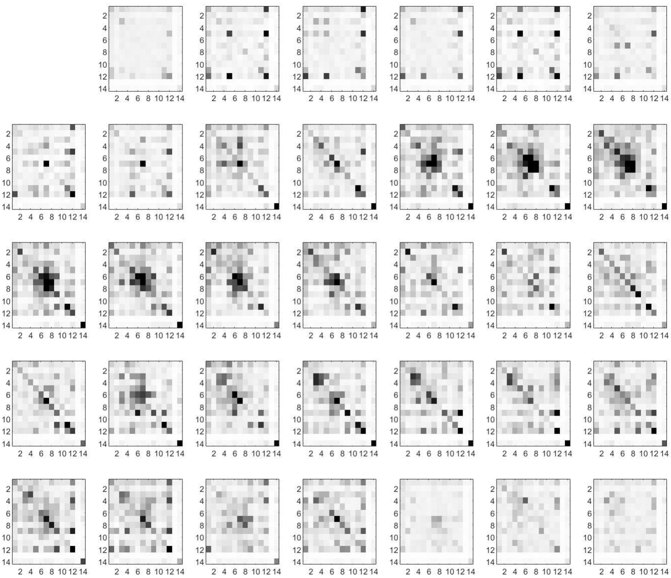

Figure 8. The traffic matrix B predictions with the Convolutional Neural Network

variable	estimate	SE	tStat	pValue
(intercept)	−89.06	248.1	-0.3590	0.7221
temperature (T)	29.97	6.925	4.327	0.00015
rainfall (R)	15.32	8.596	1.783	0.08475
wind (W)	−3.415	13.61	-0.2510	0.8035
humidity (H)	0.1109	1.152	0.09625	0.9240

Table 3. Multiple linear regression model for the number of rentals

Figure 11 shows the actual and the data predicted by the linear regression.

4.2 Genetic Programming Model

The qualities were employed in the genetic programming model. The population of organisms was 400 and the maximum number of generations was 100. Maximum permissible depth in the creation of the population which was 7. Maximum permissible depth after the operation of crossover of two organisms which was 10. Reproduction probability which was 0.3. Crossover probability which was 0.5. Maximum permissible depth after the operation of crossover of two organisms which was 10, and Maximum permissible depth after the operation of crossover of two organisms

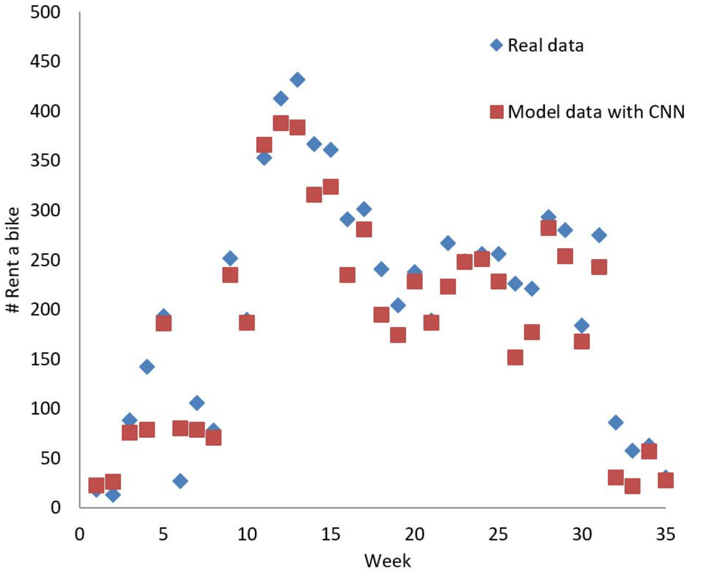

Figure 9. Real data and model data with CNNs

which was 0.5. The tournament size utilized for selecting organisms was 6 and the smallest allowable depth of organisms in producing new creatures was 2. The GP model is:

$$N = 0.15529\Bigg(5.8474R - 2W + T\Bigg(2.80398 + \frac{1}{2.48761 + \frac{T}{W-2.48761} - W} - \frac{1}{\left(T - W + \frac{T}{W-2.48761}\right)(0.1992W - 0.4)}\Bigg)\Bigg) \cdot \Bigg(T + T\Big(-2T + (83.9518 - 24.8532W)W\Big)/ \Big(-5.9353T^2 + T\Big(11.7895R - 73.7556(W - 3.40868)(W - 0.251496)\Big) + W\Big(268.153(W - 3.4057)(W - 2.92466) + R(146.503W - 494.874)\Big)\Big)\Bigg).$$

The GP model has an accuracy of 76.4 percent when comparing real and model data. Figure 12 presents the real and the GP model data.

Genetic programming gives better results than linear regression and CNNs.

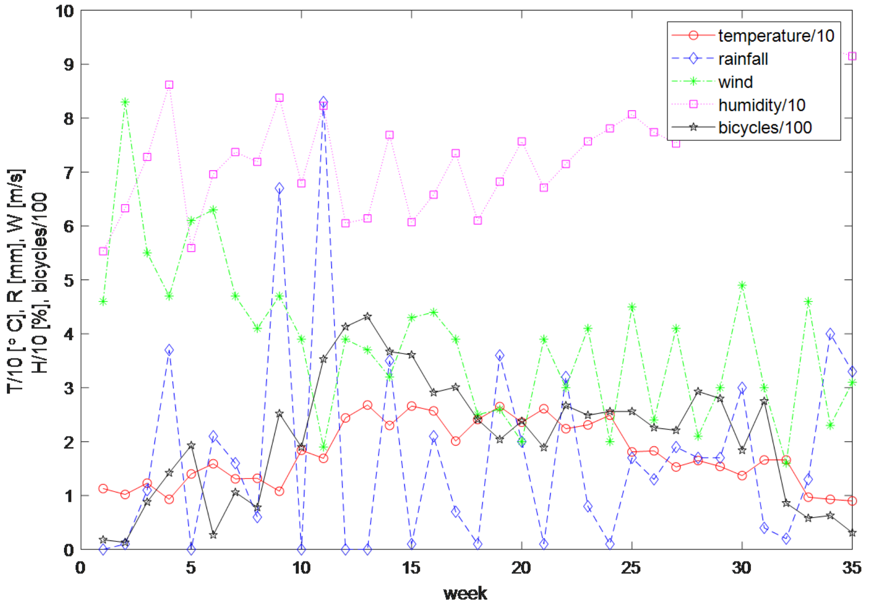

Figure 10. Weather data (temperature, rainfall, wind velocity, humidity) and the total number of bicycle rentals (bicycles). Some variables (temperature and humidity) were divided by 10 or 100 in order to better fit into a single plot

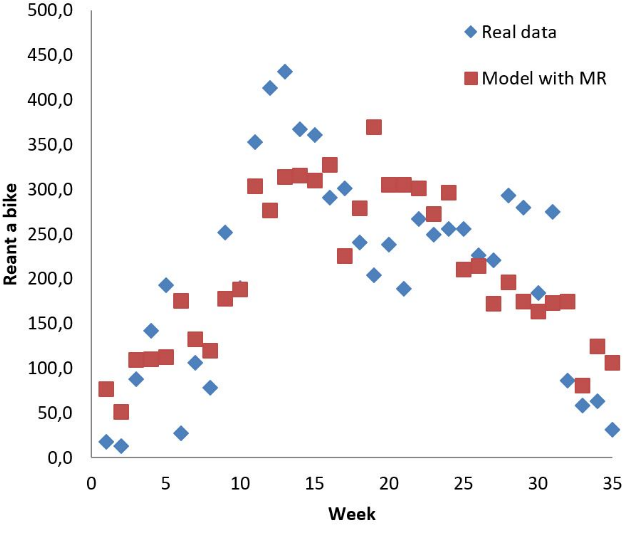

Figure 11. Real and model data with linear regression

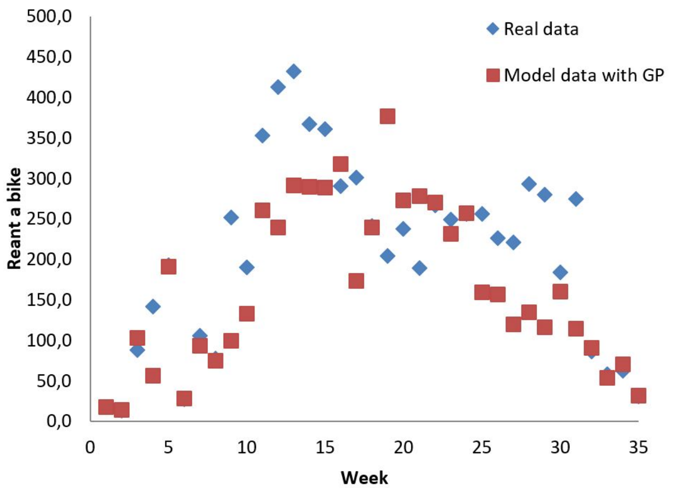

Figure 12. Real and model data with GP

5 A COMPOSITE MODEL OF CONVOLUTIONAL NEURAL NETWORKS AND GENETIC PROGRAMMING

Our results indicate that a hybrid model combining Convolutional Neural Networks and Genetic Programming is preferred, as linear regression produced the least favorable outcomes. The CNNs and GP algorithms were combined to create the composite model. As a result, a composite modeling approach is presented. It includes CNN and GP simultaneously. Each technique has its prediction in a parallel composite system. Thus, over the identical input data, CNN and GP function fully independently. An arbitration process was applied to decide the output of the parallel composite system which is the sum of the CNN and GP outputs. The results show 78.9 % accuracy between actual and model data using CNNs and GP in a composite model. Figure 13 presents real and model data with the composite model of CNN and GP.

The week with the most bike rentals (432) was the week 13. The majority of bicycles were hired between the 11th and the 17th week. Temperatures ranged from 17 to 27 degrees Celsius throughout this time. Rainfall, wind speed, and relative humidity have little effect on the price of a rented bike. Week 2 saw the fewest bikes loaned, with only 13 bikes. Thus, the average temperature this week was 11.3 °C. Between real and model data, CNNs provide 77.2 % precision. The MR model gives us an accuracy of 32.2 % when comparing real and model data. The GP model has an accuracy of 76.4 % when comparing real and model data. We get 78.9 % accuracy using the composite model of CNNs with GP.

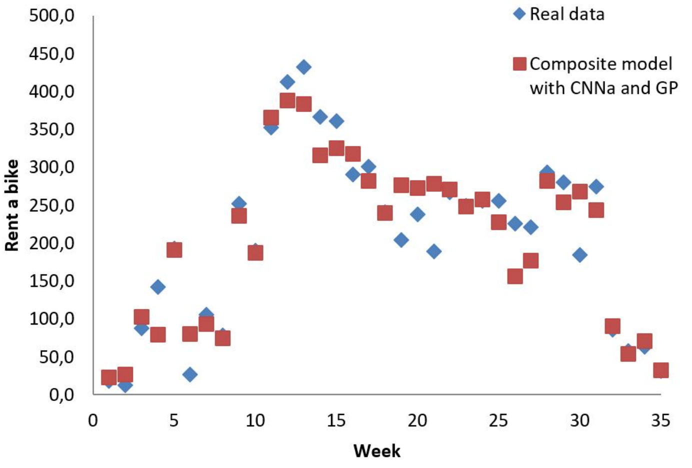

Figure 13. Real and model data with the composite model of CNN and GP

6 CONCLUSION AND FUTURE WORK

This paper presents a new approach for predicting bicycle traffic in Novo mesto, Slovenia, using convolutional neural networks and genetic programming. It was discovered that weekly bicycle rentals may be forecasted with a reasonable degree of accuracy (for 35 weeks). The impact of meteorological variables on total weekly bicycle traffic was examined using linear regression, feedforward neural networks, and genetic programming models. The GP model produces the best outcomes. Bicycling minimizes the number of cars on the road, resulting in less traffic congestion, slower driving, and lower pollution levels. Several open issues remain for future work. One of them is to develop a model of bicycle traffic system using historical data to predict bike rentals for the upcoming year. Additionally, we aim to create more methods for predictive modeling of bicycle traffic. The next open problem is identifying locations for bicycle lanes, based on bicycle travel statistics. A particularly interesting open problems is a challenge: finding new stations or new locations for bicycle rentals.

Acknowledgements

This publication is the result of the project implementation: Research on the application of artificial intelligence tools in the analysis and classification of hyperspectral sensing data (ITMS: NFP313011BWC9) supported by the Operational Programme Integrated Infrastructure (OPII) funded by the ERDF. The investment is co-financed by the Republic of Slovenia and the European Union from the European Regional Development Fund and supported by the Slovenian Research Agency (ARRS), Research program P2-0241 – Synergetic of complex systems and processes.

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