ARCHITECTURAL RESEARCH, Vol.24, No.1(March 2022). pp.1-11 pISSN 1229-6163 eISSN 2383-5575

Artificial-Neural-Network-based Night Crime Prediction Model Considering Environmental Factors

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https://doi.org/10.5659/AIKAR.2022.24.1.1

Abstract As the occurrence of a crime is dependent on different factors, their correlations are beyond the ordinary cognitive range. Owing to this limitation, systems face difficulty in correlating various factors, thereby requiring the assistance of artificial intelligence (AI) to overcome such limitations. Therefore, AI has become indispensable for crime prediction. Crimes can cause severe and irrevocable damage to a society. Recently, big data has been introduced for developing highly accurate models for crime prediction. Prediction of night crimes should be given significant consideration, because crimes primarily occur during nights, when the spatiotemporal characteristics become vulnerable to crimes. Many environmental factors that influence crime rate are applied for crime prediction, and their influence on crime rate may differ based on temporal characteristics and the nature of crime. This study aims to identify the environmental factors that influence sex and theft crimes occurring at night and proposes an artificial neural network (ANN) model to predict sex and theft crimes at night in random areas. The crime data of A district in Seoul for 12 years (2004–2015) was used, and environmental factors that influence sex and theft crimes were derived through multiple regression analysis. Two types of crime prediction models were developed: Type A using all environmental factors as input data; Type B with only the significant factors (obtained from regression analysis) as input data. The Type B model exhibited a greater accuracy than Type A, by 3.26 and 9.47 % higher for theft and sex crimes, respectively.

Keywords: Artificial Neural Network, Big Data, Smart City, CPTED, crime prediction model

1. INTRODUCTION

As crimes are becoming a serious social issue and people are increasingly anxious about them, many suggestions have been made to make a city safe. As crime methods and places are becoming diverse, government agencies are faced with challenges to analyze crime data accurately and efficiently. There is a need to introduce a strong system to process increased crime data and complex incidents and predict potential crimes in the future. In particular, as crimes often occur during nighttime, which has spatial and temporal characteristics vulnerable to crime occurrence, it is important to take nighttime crime prediction seriously. To predict crimes, environmental factors contributing to crime occurrence are often used, and these tend to have a different effect on crime occurrence depending on the time (nighttime) and type of crime. Hence, this study identifies the environmental factors contributing to nighttime sex crime and theft and propose and ANN model to predict nighttime sex crime and theft. (Included in the body text and not to be translated.)

This study used 12 years of crime data (2004 - 2015) in District A, Seoul and increased accuracy in the model by applying the significant environmental factors for sex crime and theft identified via multiple regression analysis to the ANN. The crime prediction model was compared with Type A based on overall environmental factors and Type B based on environmental factors contributing to only each type of crime. Type B increased accuracy by 3.26% for theft and 9.47% for sex crime. The prediction model holds significance as it analyzed the effect by time and type of crime beyond analyzing the correlation between crimes and environmental factors, specifically set the effect range of environmental factors, and served as a method to increase accuracy in an ANN-based prediction study.

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This research was funded by the National Research Foundation of Korea (NRF) grant funded by the Korean Government (MSIT) (No. NRF- 2018R1A2B2005528).

2. LITERATURE REVIEW

(1) Crimes and environmental factors

The use of environmental factors for crime prediction in urban spaces has been steadily increasing. According to environmental criminology, crimes do not occur randomly. They are intensive and recurrent, as they are influenced by socioeconomic, demographic, and environmental factors of an area, where the crimes are concentrated. Moreover, according to the deviation place theory, crimes are influenced by environmental factors of an area. Therefore, citizens are exposed to an environmental risk of encountering potential offenders (Newburn & Sparks, 2004).

A previous study reported differences in environmental factors between crime-prone areas and those with low crime rates (Kinney et al., 2008). Environmental factors such as public transport accessibility, land use patterns, and architecture, influence crime occurrence. It is possible to predict a crime-prone area by analyzing environmental factors that influence crimes in a city.

The daily life of people in urban spaces is significantly influenced by facilities, land use, and spatial distribution. Facilities are structures closely related to the living environment and crimes tend to be concentrated in specific facilities [15]. People's mobility toward activity nodes and facilities, such as work and school, creates patterns in their daily lives, which may render certain spaces more prone to crime [9,10]. Land use and facilities determine the zoning in terms of urban planning of Seoul, thereby exhibiting characteristic urban environments. Previously, it was reported that crimes were concentrated in specific zones of land use, and that a city's environmental factors influenced the high crime rate [11].

Land use refers to the category of activity, for which the built environment is used by the majority of people. Land use is classified based on the state, properties, and availability of land, to efficiently strategize the distribution of national land for various activities. A correlation analysis between crimes and land use patterns in Seongbuk District, in Seoul, revealed the crime occurrence areas to vary by land use [12]. This study proved that the frequency of theft crimes was high in residential, commercial (very high), and business zones. Additionally, the higher the number of floors of a building, higher was the crime rate. However, the study findings were only from correlation analysis. Mixed land use had a robust influence on crime occurrence. In Seoul, crime rates varied according to the proportion of specific uses [13]. It was determined that the crime rate increased by 30–50%, with increasing proportion of residential and commercial areas, as well as mixed land use. Therefore, an analysis of the influence of residential and commercial areas on the crime rate is essential. An analysis of the crime rate based on the clusters of land use deduced that among residential areas, apartment complexes, and detached houses, showed a positive correlation [14]. The crime rate was high in low-rise residences in A district in Seoul [14]. The rate of houses in nonresidential buildings also revealed a positive correlation to crimes. It was further deduced that early control of crimes is necessary in apartment complexes.

Furthermore, different types of facilities have been observed to influence crime rate differently. Areas with a high mixing ratio of different facilities reveal a relatively high crime rate [16]. In general, with the increasing number of residential and business facilities in an area, the crime rate drops. Furthermore, with the increasing number of commercial facilities in an area, the crime rate tended to rise and then fall. Additionally, the cost and facilities in accommodations were observed to influence the crime rate [17]; the costlier and better the perception of the material value of accommodations, the higher the probability of becoming a victim of crime. Elderly people and children are socially disadvantaged as they experience difficulty in protecting themselves against crimes; therefore, crime rate is high in facilities for the elderly and children [18]. The risk of crime occurrence was calculated based on the crime rate and awareness of space by location of crimes over a 10-year period [19]. It was deduced that entertainment establishments exhibited a high risk of crimes.

(2) Crime occurrence time and environmental factors

The effects of urban environmental factors on crime rate are influenced by time; therefore, the time of the day ought to be considered during analysis [3]. Nighttime revealed higher crime rates than daytime, as the spatiotemporal characteristics are more vulnerable to crimes at night [14]. However, these studies were limited by the difficulty in securing actual crime data in South Korea.

As illumination and visibility becomes low at night, spaces become more vulnerable to crimes at night than during the day. The presence of street lights is a primary factor considered for investigating the visibility of streets at night. A correlation analysis between crime rate and street lights revealed the distance between the lights and houses to be an influencing factor for home invasion thefts [20]. Therefore, lights can be considered to influence crime rates to a certain extent, rendering their correlation analysis necessary. The improvement of street lights increased the preventive effect toward crimes at night [21,22,23]; street lights improved the natural surveillance effect, resulting in increased crime prevention. However, the influence range of lights was not considered while considering the distance. It is difficult to determine the influence of lights through their coordinates, as the illuminance standards for street lights and security lights differ [24]. Therefore, it is necessary to set the influence range of each light according to their illuminance while analyzing their correlations with crime rate.

Closed circuit televisions (CCTVs) are generally perceived as crime prevention facilities among citizens and help reduce violent crimes [25]. Natural surveillance decreases crime rate, as it increases the chance of arrest and punishment toward potential offenders. CCTVs provide mechanical surveillance for crime prevention. Previous research on the benefits of CCTVs on crime prevention in Gangnam-gu, Seoul, found a substantial drop in crime rates such as robbery, rape, and theft in areas where CCTVs were installed and the adjacent areas. [26,27]. However, the influence of CCTVs can be different at night, as crime prevention is possible only when potential criminals perceive the presence of CCTVs. Therefore, it is necessary to specifically analyze the effects of CCTVs on crimes [28,29].

Street trees have been shown to influence crime rate by limiting visibility. A previous study analyzed the illuminance of outdoor spaces in residential areas, where street trees were planted; the illuminance of the space was generally constant. However, there was a risk of crimes in spaces, where visibility was obscured by trees or street facilities owing to low illuminance [30]. The influence of street trees in cities was analyzed through clustering, which revealed that street trees provided hiding places for criminals and decreased the illuminance, thereby limiting visibility. Under poor maintenance, they increased the disorderliness of streets owing to fallen leaves and roots [31].

Public transportation facilities such as bus stops can act as a factor causing crimes, owing to the floating population using public transport [32.33]. These facilities fester conditions for potential criminals, mixing with the crowd in public transports, for criminal opportunities. A correlation study between bus stops and crime rate, according to time, reported that crimes occurred disproportionately during busy hours: late afternoons and early evenings. However, severe violent crimes occurred at nights and early mornings, when the number of pedestrians at bus stops was low [34]. Therefore, bus stops can be considered to impose a different influence on crime rate, based on temporal characteristics.

The infamous South Korean serial killer Ho-sun Kang, who killed 10 women between September 2006 and December 2008, lured women to bus stops located in the outskirts of the capital area. At nights, bus stops are places with a high risk of crime [35]. Therefore, clear correlations are required between bus stops characteristics and crime rate, as bus stops are specifically targeted by criminals.

(3) Artificial-neural-network-based nighttime sex and theft crime prediction models

An ANN is a network algorithm based on interconnected artificial neurons emulating brain neural networks. It is increasingly used for crime prediction modeling, considering its excellent predictive power. The ANN model increases the accuracy of prediction models through domain nodes and hidden layers, yielding predictions with higher accuracy than conventional mathematical implementation based on existing statistics [35]. A study employing an ANN crime prediction model of an area with a high crime rate [36] noted the model's efficiency in identifying urban crime trends and its high crime prediction accuracy. Such studies have confirmed the goodness-of-fit of ANN models as crime prediction models.

ANN models demonstrate a higher crime prediction accuracy when the time and location data of crime are used based on the place, pattern, and time by geographic area [37,38]. Thus, the model accuracy can further improve when additionally trained with the locational data of actual crime scenes across the city and factors associated with crimes. Accordingly, this study presents a crime prediction model for each crime type based on nighttime urban environmental factors.

3. MATERIALS AND METHODS

This section describes the method used to analyze the impact of factors associated with crime. First, this study established a database using data on nighttime sexual and theft crimes and physical environmental factors of Dongjak-gu with the cooperation of the Seoul Metropolitan Police Agency. Second, it conducted a multiple regression analysis using the established database, followed by the extraction of factors influencing sex and theft crime. Third, it constructed prediction models for nighttime sex and theft crimes using significant variables as the input data for the ANN model.(1) Crime statistics of Dongjak-gu, Seoul

We analyzed crime data from the Seoul Metropolitan Police Agency for an overview of the current state of crime in Dongjak-gu, Seoul. According to the 2011–2015 crime occurrence data, violent crime incidents increased by an annual average of 350 cases from 2011 to 2013. A decreasing trend was observed in 2014 and 2015; however, sex crime incidents began to increase throughout the analysis period, reaching 150 cases in 2015. The percentage of sex crimes relative to all violent crime incidents also increased, reaching 3.77% in 2015. With a total of 3,981 cases of violent crime in 2015 (i.e., over 10 cases per day on average), anticrime efforts are necessary to create a safe urban environment.

Table 1. Data on the type of crimes committed in Dongjak-gu, Seoul (2011–2015).

Period	Sum	Murder	Robbery	Sex Crime	Theft	Assault
2011	3,711 (100%)	8 (0.2%)	19 (0.5%)	91 (2.5%)	1,548 (41.7%)	2,045 (55.1%)
2012	4,237 (100%)	2 (0.05%)	13 (0.3%)	130 (3%)	2,040 (48.1%)	2,052 (48.4%)
2013	4,413 (100%)	8 (0.2%)	7 (0.2%)	121 (2.7%)	2,320 (52.6%)	1,957 (44.3%)
2014	4,070 (100%)	5 (0.1%)	8 (0.2%)	137 (3.4%)	1,939 (47.6%)	1,981 (48.7%)
2015	3,981 (100%)	6 (0.1%)	9 (0.2%)	150 (3.77%)	1,856 (46.6%)	1,960 (49.2%)

Although Dongjak-gu is the 24th most densely populated of 25 autonomous districts in Seoul, with a commercial area accounting for 2.1% of the total area, its crime rate is high. Despite being a typical residential area, Dongjak-gu has a high crime rate, owing to the district's delayed regional development relative to the surrounding areas, which has resulted in poor infrastructure (e.g., arterial roads) and remnants of the old downtown dispersed throughout the district, such as narrow and secluded alleys and areas dense with detached houses [39].

According to a study analyzing crime hotspots in Seoul based on the frequency of the five major crimes per square kilometer and evaluating the safety level of 25 autonomous districts in Seoul [40], a hotspot was defined as an area satisfying the reference numbers of five major crimes committed per year, with a point assigned to each item exceeding the reference number: 105 assaults, 0.3 murders, 1.6 robberies, 69.7 thefts, and 0.6 sex crimes. The higher the score, the higher the area crime risk [40]. Dongjak-gu, Seoul, is classified as a very dangerous area requiring crime prevention through environmental design.

(1) Crime analysis subjects

It is necessary to classify crime by five major crime types considering variances in place, time, and method of crime by factors associated with respective crime types (murder, robbery, theft, assault, and sex crime). Thus, this study analyzes the impact of each urban environmental factor on nighttime sex and theft crimes.

(2) Crime occurrence data

We used crime data for 2004–2015 with the cooperation of the Seoul Metropolitan Police Agency. The locational data for 9,407 theft and 1,069 sex crime cases were extracted from the database of five major violent crimes recorded by the local police station in Dongjak-gu. After excluding samples with unclear locational data, 5,638 nighttime theft and 830 nighttime sex crime incidents were included in the analysis. A crime data point includes concrete information on date and time, crime type, and crime scene location and address. The extracted crime scene locational data were converted into map coordinates through geo-coding, followed by QGIS analysis. We used related data of the same year to analyze environmental factors and retrieved basic data from the Seoul Open Data Portal: Dongjak-gu has 9,713 security lights, 2,905 street lights, 566 CCTVs, 257,235 street trees, and 519 bus stops.

We forwarded a query on street lighting to the Seoul Metropolitan Facilities Management Corporation Road Division to set the time window and received confirmation that Seoul's street lights and security lights were turned on and off 15 min after sunset and sunrise, respectively. Thus, with the sex and theft crime QGIS analysis data from the 10-year comprehensive analysis of crime, we set the time window of crime occurrence as 19:00 to 06:00 to analyze the nighttime impact on sex and theft crimes.

(3) Extraction of meaningful factors through multiple regression analysis

We conducted a multiple regression analysis using the IBM SPSS Statistics 25 program to extract factors associated with sex and theft crimes committed at night. Equation (1) describes the multiple regression analysis. The dependent variable ($\boldsymbol{Y}$) captured the sex and theft nighttime crimes and the independent variable ($\boldsymbol{x_k}$) captured environmental factors (physical factors, land use, and facilities data) to estimate the coefficient of determination ($\boldsymbol{\beta_k}$) and the constant term of the model ($\boldsymbol{\beta_0}$).

$$\boldsymbol{Y} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 x_1} + \boldsymbol{\beta_2 x_2} + \cdots + \boldsymbol{\beta_k x_k} \tag{1}$$

In the next subsection, we derive significant factors for crime occurrence and construct the nighttime sex and theft crime prediction models using input data for the ANN-based crime prediction.

(4) Selection of Multiple Regression Variables

We used street lighting, CCTV, street trees, bus stops, land use, and facilities data as control variables to investigate correlations between nighttime sex and theft crimes and urban environmental factors. We categorized them into physical factors, land use, and facilities to obtain clearer analysis outcomes. The Korea National Spatial Data Infrastructure Portal provided land use and facility data, and the data on street lights, security lights, CCTV, street trees, and bus stops were retrieved from the Seoul Open Data Portal.

We used the respective locational data of street lighting, CCTV, street trees, and bus stops to analyze the impact of the physical factors. We set the range of influence of street lighting according to the horizontal plane illuminance of street and security lights, following prior research and the system management rules of security lighting in Dongjak-gu [43]. With horizontal plane illuminance standards of 10–20 lx (the appropriate horizontal illuminance value range for streetlights installed along main roads) and 3–5 lx (the horizontal plane illuminance standard for security lights), we set the range of influence of street lights to 10m and security lights to5 m.

Land use can be classified into residential, commercial, and green zones. The residential zone is subdivided into Classes 1 to 3 general residential areas and quasi-residential zones. Commercial zones are classified into neighborhood, distribution, and general commercial districts. The green zone is natural green spaces. In the residential zone, Classes 1 to 3 general residential areas are characterized by low-, medium-, and medium-high-rise houses, respectively. The quasi-residential zone is a residential area with partial permission for commercial and business activities. In the commercial zone, the neighborhood commercial district promotes intra-city and inter-district distribution services. Daily necessities and services are supplied in the distribution commercial district. The general commercial district accommodates general commercial and business functions. The natural green space of the green zone is a limited development area for green space protection.

The facilities data were initially classified 16 items according to the purpose of use to obtain more accurate research results: detached houses, multifamily housing, education and research facilities, commercial facilities, lodging facilities, adult entertainment facilities, business facilities, police agencies and stations, public facilities, facilities for senior citizens and children, religious facilities, medical facilities, factories, parking lots, cemetery facilities, obnoxious facilities, and warehouses. A detached house is built for one or several households; each unit has one or more rooms, a kitchen, an entrance, and a toilet for independent dwelling. In multifamily housing (e.g., apartment houses and townhouses), all or part of the walls, hallways, stairs, or other building facilities are used jointly by two or more households. Education and research facilities are used for educational activities; commercial facilities, commercial activities; lodging facilities, accommodating tourists and travelers; and adult entertainment facilities, enjoyment and entertainment, such as drinking, dancing, and singing (e.g., entertainment pubs, karaoke bars, and nightclubs).

Business facilities are used for business activities; police agencies and stations, police administration and public security; public facilities, pursuing the common good of society; facilities for senior citizens and children, social welfare, and labor welfare (e.g., youth camps and senior welfare centers); religious facilities, religious gatherings; medical facilities, patient care; parking lots, safe parking of cars; cemetery facilities, funeral and burial (e.g., ossuaries); warehouses, storing materials and objects; and obnoxious facilities, disgusting and polluting facilities (e.g., landfills, nuclear power plants, and incinerators).

(5) Selection of Analysis Units

Prior studies have analyzed correlations between urban environmental factors and crime locations via census and administrative units. However, there is an increasing demand for a more efficient analysis unit to ensure uniform calculation results across wide areas [44].

Thus, we analyzed the urban physical environment in grid units. Relative to administrative or census units, grids have the same shape and size, thus enabling objective interpretation of statistics and microscopic analysis through flexible map scaling. We applied the standard 100 × 100 intervals used for land aptitude evaluation for the grid size, which is an evaluation system for similar city planning.

(6) Artificial neural network

An ANN simulates human information processing. It collects new data by detecting discernable patterns and relationships in the training data and learning through experience rather than programming [45]. Further, ANN can handle data more flexibly than conventional statistical approaches and addresses the limitations of input and output data considering the systemic complexity of current statistical prediction models.

Minsky and Papert [46] noted that early-phase ANN models were criticized for excessive simplification by ignoring the nonlinearity of data and the difficulty associated with the exclusive-or problem. However, the deep neural network (DNN) approach addressed this problem with an increase in the numbers of hidden layers and interlayer connections and a change in the topological structure of the network, thereby enhancing the learning ability [47,48]. With a DNN model with one or more hidden layers, it is possible to learn a vast amount of untapped data and construct a prediction model for output estimation with the weight of each node [49].

$$\boldsymbol{n_k^h} = \sum_{j=1}^{R} \boldsymbol{w_{k_j}^h p_j} + \boldsymbol{b_b^k \cdot k} = \boldsymbol{1 to S} \tag{2}$$

This Equation (2) presents the basic ANN model used in this study. R is the number of input variables, S is the number of hidden neurons, p is an input variable, b is a hidden layer, and w is the model weight. Each calculated weight is used as an input of the activation function, and the output is estimated as the sum of the weighted values [50]. This study employed the most basic sigmoid function as the activation function.

For an accurate ANN-based crime prediction model, hidden nodes and layers should be considered. However, as there are no clear model construction methodologies and criteria, an optimal model with the lowest mean squared error (MSE) value should be derived after constructing as many models as possible. The model is constructed as follows: The minimum number of hidden nodes and layers must be greater than the number of input variables, and the maximum number should not exceed 2n + 1 to ensure efficient learning [51], where n is the number of input variables. This study compared and analyzed up to six models starting from a one-layer neural network and adding one layer after another in succession. In the configuration of the numbers of layers and hidden nodes of each model, the model with the lowest MSE value is selected from among three to five cases of each of the minimum, medium, and maximum models.

For performance verification of the nighttime sex and theft crime prediction models, the input data are composed in two ways for performance comparison. Accordingly, two models were prepared as follows: a model using factors influencing crime derived from previous studies as input data, and a model using significant factors influencing crime determined by regression analysis.

A comparison of the ANN models for nighttime sex crime and theft revealed that Type B based on only the factors identified as significant via multiple regression analysis had a higher level of accuracy than Type A based on overall factors contributing to nighttime sex crime and theft.

The accuracy of the Type B prediction model was higher by 3.26% and 9.47% for theft and sex crimes, respectively.

4. RESULTS

(1) Extraction of environmental factors

The variable composition includes four physical factors, eight land uses, and 16 facilities. Table 2 presents the results of the descriptive statistics for each variable verified to impact nighttime theft and sex crimes conducted before correlation analyses of the physical environmental factors influencing crime with sex and theft crimes. Before analysis, a multicollinearity analysis was performed. A tolerance greater than 0.1 and VIF less than 10 indicate no multicollinearity among independent variables [52]. The VIF values were less than 5 in the multiple linear regression; thus, no multicollinearity was found.

Table 3 shows that the Durbin-Watson test for autocorrelation

Table 2. Variable composition, descriptive statistics, and variance inflation factor (VIF) values for impact analysis of nighttime sex and theft crimes.

Category	Code	Mean	Standard deviation	N	Common difference	VIF
Land use	Class 1 general residential area	2182.45	3457.953	1,773	.310	3.222
	Class 2 general residential area	3290.77	3969.789	1,773	.238	4.207
	Class 3 general residential area	2107.82	3230.624	1,773	.325	3.078
	Quasi-residential zone	114.23	766.223	1,773	.822	1.217
	Neighborhood commercial district	17.68	246.137	1,773	.921	1.086
	Distribution commercial district	26.42	392.337	1,773	.962	1.040
	General commercial district	175.50	917.333	1,773	.741	1.350
	Natural green space	1277.61	3090.401	1,773	.335	2.984
Facilities	Detached houses	8.76	14.317	1,773	.672	1.489
	Multifamily housing	3.42	5.220	1,773	.736	1.358
	Education and research facilities	.15	.563	1,773	.920	1.087
	Commercial facilities	1.59	3.255	1,773	.525	1.903
	Lodging facilities	.01	.095	1,773	.874	1.145
	Adult entertainment facilities	.01	.118	1,773	.860	1.163
	Business facilities	.34	.867	1,773	.666	1.502
	Police stations	.00	.047	1,773	.985	1.015
	Public facilities	.06	.272	1,773	.952	1.050
	Facilities for senior citizens and children	.06	.237	1,773	.953	1.049
	Religious facilities	.14	.449	1,773	.945	1.058
	Medical facilities	.07	.322	1,773	.850	1.177
	Factories	.00	.034	1,773	.973	1.028
	Parking lots	.00	.053	1,773	.987	1.013
	Facilities related to cemeteries	.02	.159	1,773	.926	1.080
	Obnoxious facilities	.01	.103	1,773	.944	1.060
	Warehouses	.01	.106	1,773	.992	1.008
Physical factors	CCTV	2.32	1.403	1,773	.980	1.021
	Street light	572.46	752.300	1,773	.775	1.290
	Street tree	3.85	7.702	1,773	.674	1.483
	Bus stop	.29	.697	1,773	.771	1.297

yielded a value close to 2 (1.954–2.032), indicating that there was no autocorrelation. The explanatory power of each model was 19.9% for theft and 13.3% for sex crime prediction models. Cohen's f2, generally used in statistical analyses in the social sciences, is a measure of effect sizes used when performing F-tests in analysis of variance or multiple regression analysis. As per Cohen's standard, $R^2 = 0.02$ indicates a small effect, $R^2 = 0.13$ a medium effect, and $R^2 = 0.26$ a large effect. Thus, with the values of the multiple regression model ranging between 0.133 and 0.199, the study's explanatory power is sufficient.

Table 3. Explanatory power and model fit analysis results

	R	R^2	Revised R^2	Estimated Standard error	Durbin-Watson	F	P
Theft	0.446	0.199	0.186	6.047	1.955	15.460	0.000
Sex Crime	0.321	0.133	0.109	1.726	2.033	7.018	0.000

Table 4 presents urban environmental factors influencing nighttime sex and theft crimes determined by the regression analysis, and the urban environmental factors influencing nighttime sex and theft crimes. Appendix A presents detailed analysis results. If the p-value derived through multiple regression analysis (confidence interval) is less than 0.10, its significance is established in 90% of the total cases; if less than 0.05, 95%; and if less than 0.01, 99%.

Table 4. Significant variables extracted by crime type and environmental factor.

Category	Code	Theft	Sex Crime
Land use	Class 1 general residential area		
	Class 2 general residential area	O	O
	Class 3 general residential area	O	
	Quasi-residential zone	O	
	Neighborhood commercial district		O
	Distribution commercial district		
	General commercial district	O	O
	Natural green space		
Facilities	Detached houses		
	Multifamily housing		
	Education and research facilities		
	Commercial facilities	O	O
	Lodging facilities		O
	Adult entertainment facilities	O	
	Business facilities	O	O
	Police stations		
	Public facilities		
	Facilities for senior citizens and children		O
	Religious facilities		
	Medical facilities		
	Factories		
	Parking lots		
	Facilities related to cemeteries		
	Obnoxious facilities		
	Warehouses		
Physical factors	CCTV		
	Street light	O	
	Street tree		
	Bus stop		
Total		8	7

Environmental factors influencing sex and theft crimes at night were first identified through regression analysis. A significant correlation was observed between the land use and sex and theft crime rates; both crimes were frequent at nights in Type 2 general residential areas, general commercial areas, and business facilities. This supports the results of a previous study that reported a high probability of violent crimes in residential, commercial, and business areas [12].

Theft crime rate at night was high in Type 3 general residential areas and entertainment facilities in semi-residential areas, and was influenced by the presence of street lights. Type 3 general residential areas with mid to high-rise residential buildings positively correlated with theft crimes at night. This supported the results of a previous study [54], where large apartments with low visual connection to surrounding streets increased the theft crime rate on streets [54]. It was observed that the risk of theft crimes was high at night, as visibility is reduced compared to daytime, and natural surveillance from apartments decreases.

Semi-residential areas are those with the highest commercial characteristics among residential areas, where residence and commerce are mixed. Results related to these areas supported those of a previous study [13], where the crime risk increases with increased mixing of residential and commercial elements. Entertainment facilities exhibit a high violent crime rate. Recreational zones in Seoul are designated as public security reinforcement zones, as low-income groups are concentrated [15]. Street lights were positively correlated with the reduction of crime rate, confirming their effect on preventing theft crimes. This supports the finding of a previous study [21], where street lights maximized natural surveillance effect, thereby decreasing the crime rate.

The land use patterns that influenced sex crimes at night, individually, were neighborhood commercial areas, accommodations, and facilities for the elderly and children. Neighborhood commercial areas are areas where small-scale commercial and business facilities are located in proximity to residential areas. The study findings revealed that commercial and business facilities near residential areas exhibited a high risk of sex crimes at night. This supports the results of a previous study, where the mix of residential and commercial areas exhibited a high risk of crimes [12], and where the sex crime rate was high in accommodations [15]. The correlation results of welfare and educational facilities for elderly people and children were in agreement with those of a previous study, where the crime rate was high in facilities for elderly people and children [18].

(2) ANN-based analysis

This result is highly significant for research and practical applicability. In the development of a prediction model using ANN, the risk of overfitting increases with the increasing number of variables. The probability of overfitting was reduced in our study. If an ANN model is developed through multiple regression analysis in advance, for a crime prediction model based on urban environmental factors in the future, a model with a higher explanatory power could be designed. The crime prediction model developed in this study can contribute to establish proactive response measures, optimized to each crime type, according to urban environmental and spatiotemporal factors, in the near future.

We constructed an ANN model for two crime types (nighttime theft and sex crimes) and performed analyses where factors influencing them were set as variables. The input variables for the crime prediction model based on factors significantly associated with their respective crime types comprised eight theft- and seven sex-related crime variables.

After excluding outliers, we employed 1,773 data points for analysis, of which 1,241 were used as the training set, 266 as the validation set, and 266 as the testing set (Table 5).

Table 5. Data allocation.

Sample	Training	Validation	Testing
1,773	70%	15%	15%
	1,241	266	266

Table 6 presents the results of the performance comparison of the four best-performing nighttime theft and sex crime prediction models by layer and node composition. Using more layers than presented in the table resulted in a vanishing gradient, thereby making it unsuitable as a prediction model.

Table 6. Hidden layer composition-dependent performance of the crime prediction model type A.

Crime Type	Min	Max	Layer	Neuron	R-Value of Training	R-Value of Validation	R-Value of Test	MSE	Terminated Epoch
Theft	8	17	1	8	0.4447	0.4409	0.3087	7.2509	3rd
				12	0.4074	0.4202	0.3359	3.7766	6th
				15	0.3229	0.2365	0.2064	6.0822	13th
			2	4	0.3814	0.3967	0.6929	8.3148	7th
				6	0.4139	0.5701	0.4669	7.2339	11th
				8	0.43315	0.4449	0.5543	6.2252	5th
			3	3	0.3697	0.3286	0.4983	9.1109	2nd
				4	0.431	0.3692	0.3824	5.6412	4th
				5	0.4459	0.3507	0.4072	9.7707	16th
			4	2	0.4478	0.1626	0.3193	8.1912	3rd
				3	0.4004	0.4179	0.3816	5.6412	5th
Sex Crime	7	15	1	9	0.3149	0.4693	0.4763	1.1233	12th
				11	0.2130	0.2442	0.2996	1.2814	11th
				14	0.2544	0.4889	0.5096	1.1278	2nd
			2	4	0.3312	0.2658	0.2687	1.0372	10th
				5	0.3214	0.2842	0.2352	2.3968	11th
				7	0.3198	0.3707	0.3438	0.8917	5th
			3	3	0.2265	0.4334	0.3006	1.4939	5th
				4	0.2661	0.3569	0.2927	3.0096	13th
			4	2	0.2989	0.3337	0.2334	1.1827	4th
				3	0.3412	0.2181	0.2626	1.0509	3rd

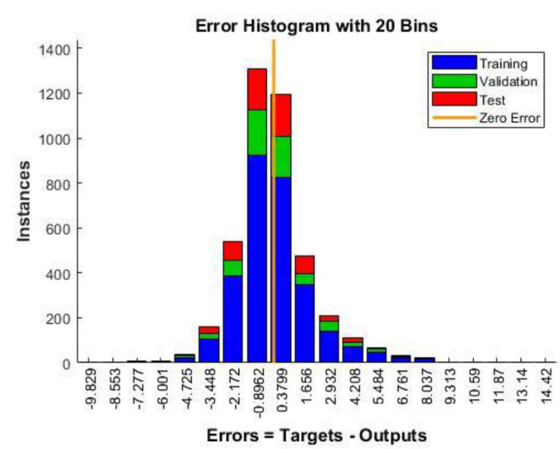

Figure 1. Nighttime theft crime prediction model (Layer: 1, node: 12): (a) Training data regression result; (b) Validation data regression result; (c) Test data regression result.

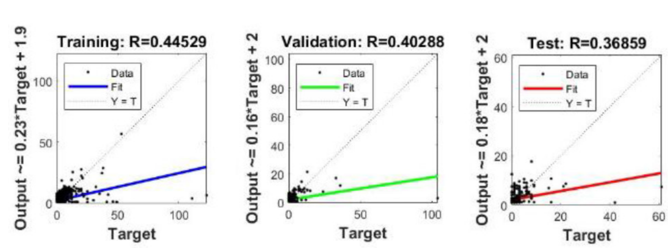

Figure 2. Nighttime theft crime prediction model

Figure 1 presents the graphs for the R-values of the training, validation, and test sets of the best-performing nighttime theft crime prediction models (0.4074, 0.4202, and 0.3359, respectively). The ANN model outperformed the other models with an MSE value of 102x0.3.7766, one layer, and 12 nodes.

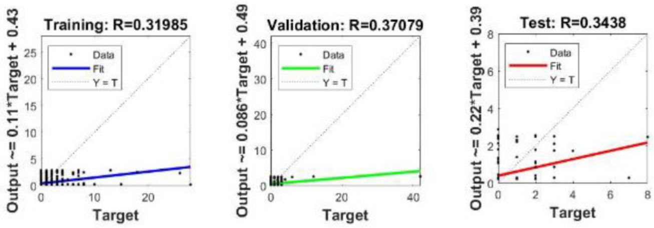

Figure 3. Nighttime sex crime prediction model (Layer: 21, node: 7): (a) Training data regression result; (b) Validation data regression result; (c) Test data regression result.

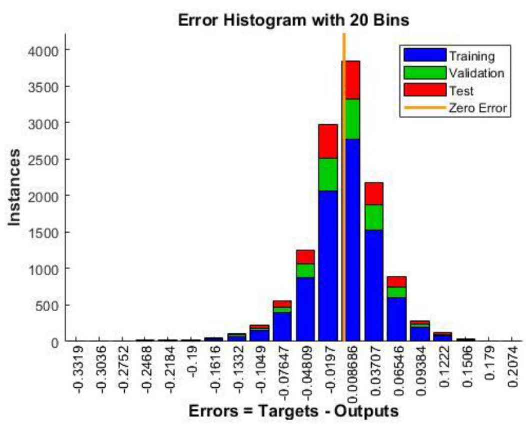

Figure 4. Nighttime sex crime prediction model

Figure 2 presents the graphs for the R-values of the training, validation, and test sets of the best-performing nighttime sex crime prediction models (0.3198, 0.3707, and 0.3438, respectively). The ANN model outperformed the other models with an MSE value of 102x0.8917, two layers, and seven nodes.

Table 7 compares the predictive power of the models with different input data configurations. Type A's input data comprises 28 factors from the three factor groups (land use, facilities, and physical factors) found to jointly influence crime occurrence in previous studies. Type B's input data comprise only significant theft and sex crime factors derived from the regression analysis.

Table 7. Performance of the crime prediction model by crime type depending on input data composition.

Period	Input Type	Layer	Neuron	R-Value of Training	R-Value of Validation	R-Value of Test	MSE	Terminated Epoch
Theft	A	1	12	0.4452	0.4028	0.3685	4.5677	7th
	B	1	12	0.4074	0.4202	03359	3.7766	6th
Sex Crime	A	2	7	0.2998	0.1368	0.2491	0.9161	8th
	B	2	7	0.3198	0.3707	0.3438	0.8917	5th

Further, we retained the numbers of layers and neurons for Types A and B to control the influence of factors other than the input data of each model. A comparison of the ANN model revealed that Type B, trained with the input data comprising significant factors from the regression analysis in both nighttime theft and sex crime prediction models, outperformed Type A per the MSE values. The accuracy of the Type B prediction model was higher by 3.26% and 9.47% for theft and sex crimes, respectively.

4. DISCUSSION

This study was intended to identify environmental factors contributing to nighttime sex crime and theft in District A, Seoul and subsequently propose an ANN model that can predict such crimes in any area. Based on previous studies, environmental factors had a different effect during nighttime compared to daytime, and accordingly, this study focused on their effect during nighttime and set the time range of environmental factors. Multiple regression analysis was conducted to analyze the effect of environmental factors on sex crime and theft. The results confirmed that they had a different effect on a different type of crime, and the effect level and importance of the factors for each type of crime was identified. Focusing on nighttime with an environment vulnerable to crimes and identifying environmental factors contributing to sex crime and theft would help to respond to potential crimes during nighttime, in which violent crimes are more than twice as likely to occur as during daytime. If patrol personnel and methods are determined depending on the risk of crime, and limited police manpower is allocated more efficiently based on these results, it would be possible to prevent crimes preemptively, arrest criminals quickly, and thereby provide a safe urban environment to citizens.

The multiple regression analysis enabled the identification of environmental factors that differently influence sex and theft crime rate at night. The primary discovery was that the occurrence of sex and theft crimes at night were significantly influenced by the degree of mixing of residential and commercial areas, and the separation or adjacency to each other. Semi-residential areas with mixed residential and commercial facilities increased the theft crime rate at night. Neighborhood commercial areas where small-scale commercial and business facilities are located near residential areas increased the sex crime rate at night. When commercial and residential facilities were separated, it influenced both sex and theft crimes. Among the environmental factors, CCTVs improved the crime prevention effect, but had no influence on crimes at night. This result indicates that CCTVs have a crime prevention effect when they are visible to criminals. Therefore, signs that indicate the presence of surveillance cameras (CCTVs) are required at night. Therefore, the influence of urban environmental factors on the occurrence of sex and theft crimes at night differed significantly. The accuracy of prediction increased when the ANN-based crime prediction model was developed by using factors exhibiting significant effects on each type of crime.

A total of two types of prediction models for sex crime and theft were compared to determine whether they fit as the crime prediction model. Type A used overall environmental factors as input data, while Type B used only the significant environmental factors for each type of crime identified via regression analysis as input data. A comparison of accuracy revealed that Type B had a higher level of accuracy. Since the accuracy of the prediction model increased by 3.26% for theft and 9.47% for sex crime, these results are considered fairly meaningful. A higher number of variables is more likely to lead to overfitting in building an ANN-based prediction model. By preemptively identifying and using significant variables for each type of crime with multiple regression analysis, it was confirmed that it decreased a possibility of overfitting while increasing accuracy in the model. If multiple regression analysis is conducted first and then the ANN model is built, it would help to design a model with a higher level of explanatory power. In the future, the predictions herein can contribute to establishing response measures optimized for each type of crime based on urban environmental factors and spatial characteristics. In addition, it may serve as a reference for a future study to set policies related to CPTED and explore how to institutionalize them. This study holds significance as it investigated more accurate ANN prediction by using significant environmental factors identified via regression analysis, instead of simply predicting crimes.

The study findings could be used as basic data for establishing and institutionalizing the crime prevention through environmental design (CPTED)-related policies in follow-up studies.

The analysis presented in this study is limited to the influence of environmental factors on crimes. However, crimes are caused by the complex influence of social, economic, and environmental factors. This study primarily considered environmental factors, as it is a basic study for building an ANN

Appendix A

Table A1. Factors influencing nighttime theft crime: extraction results.

Category	Theft				
	Unstandardized coefficient		Standardized coefficient	t	P
	B	Standard error			
Terminology	.326	.669		.486	.627
Class 1 general residential area	5.549E−5	.000	.029	.744	.457
Class 2 general residential area	.000	.000	.083	1.890	*.059
Class 3 general residential area	.000	.000	.062	1.656	*.098
Quasi-residential zone	.001	.000	.065	2.762	**.006
Neighborhood commercial district	.001	.001	.024	1.091	.275
Distribution commercial district	8.045E−5	.000	.005	.216	.829
General commercial district	.001	.000	.145	5.818	***.000
Natural green space	7.730E−7	.000	.000	.010	.992
Detached houses	.002	.012	.001	.143	.886
Multi-family housing	.003	.032	.002	.079	.937
Education and research facilities	−.080	.266	−.007	−.299	.765
Commercial facilities	.477	.061	.231	7.830	***.000
Lodging facilities	1.863	1.624	.026	1.147	.252
Adult entertainment facilities	6.284	1.312	.111	4.791	***.000
Business facilities	.574	.203	.074	2.827	**.005
Police stations	.881	3.048	.006	.289	.773
Public facilities	−.135	.541	−.005	−.249	.803
Facilities for senior citizens and children	.628	.621	.022	1.012	.312
Religious facilities	.460	.329	.031	1.398	.162
Medical facilities	.757	.484	.036	1.563	.118
Factories	−2.939	4.337	−.015	−.678	.498
Parking lots	−.666	2.724	−.005	−.244	.807
Facilities related to cemeteries	−.001	.942	.000	−.001	.999
Obnoxious facilities	−.611	1.432	−.009	−.427	.670
Warehouses	−.113	1.360	−.002	−.083	.934
CCTV	−.131	.103	−.027	−1.263	.207
Street light	.000	.000	−.042	−1.736	*.083
Street tree	−.001	.023	−.002	−.060	−953
Bus stop	.283	.235	.029	1.206	.228

Note. * 90% Confidence interval (p-value < 0.10)
** 95% Confidence interval (p-value < 0.05)
*** 99% Confidence interval (p-value < 0.01)

Table A2. Factors influencing nighttime sex crime: extraction results.

Category	Sex Crime				
	Unstandardized coefficient		Standardized coefficient	t	P
	B	Standard error			
Terminology	.016	.191		.086	.932
Class 1 general residential area	1.977E−5	.000	.038	.930	.353
Class 2 general residential area	4.459E−5	.000	.098	2.107	**.035
Class 3 general residential area	2.458E−5	.000	.044	1.105	.269
Quasi-residential zone	7.520E−5	.000	.032	1.275	.202
Neighborhood commercial district	.000	.000	.049	2.055	**.040
Distribution commercial district	−1.690E−6	.000	.000	-.016	.987
General commercial district	.000	.000	.103	3.914	***.000
Natural green space	6.613E−6	.000	.011	.289	.773
Detached houses	.004	.003	.029	1.052	.293
Multi-family housing	−.002	.009	-.005	-.199	.842
Education and research facilities	−.046	.076	-.014	-.601	.548
Commercial facilities	.072	.017	.131	4.174	***.000
Lodging facilities	.984	.463	.052	2.123	**.034
Adult entertainment facilities	.301	.374	.020	.804	.422
Business facilities	.180	.058	.086	3.104	**.002
Police stations	.909	.870	.024	1.046	.296
Public facilities	−.042	.154	-.006	-.272	.785
Facilities for senior citizens and children	.390	.177	.051	2.203	**.028
Religious facilities	.124	.094	.031	1.323	.186
Medical facilities	.144	.138	.026	1.041	.298
Factories	−1.379	1.237	-.026	-1.115	.265
Parking lots	−.367	.777	-.011	-.472	.637
Facilities related to cemeteries	−.015	.269	-.001	-.057	.955
Obnoxious facilities	−.058	.409	-.003	-.142	.887
Warehouses	−.322	.388	-.019	-.830	.406
CCTV	−.035	.029	-.027	-1.185	.236
Street Light	−4.380E−5	.000	-.018	-.708	.479
Street tree	.005	.006	.023	.828	.408
Bus stop	.058	.067	.022	.863	.388

Note. * 90% Confidence interval (p-value < 0.10)
** 95% Confidence interval (p-value < 0.05)
*** 99% Confidence interval (p-value < 0.01)

prediction model based on the correlation between crimes and environmental factors identified through multiple regression analysis. Furthermore, this study excluded the influence factors that have not yet been converted to data, as factors such as garbage on the street and broken street lights that can influence actual crimes by increasing the disorderliness of cities are difficult to predict and convert to data. The current analysis was conducted based on the location data of environmental factors that influence crimes. A follow-up study implementing a crime prediction model by using a diverse set of factors by overcoming these limitations could enable advanced and sophisticated crime prediction.

In the future, this model is expected to contribute to predicting and preventing crimes more accurately if used to designate patrol routes based on the land use. To prevent nighttime theft, it is necessary to patrol areas that include both residential and commercial zones. To prevent nighttime sex crime, it is important to focus on the areas where commercial and business facilities are located and there are residential zones nearby. To prevent both sex crime and theft, there is a need to designate patrol routes for the areas where residential and commercial zones are located separately. Then, it would be possible to prevent nighttime sex crime and theft.

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(Received Feb. 3, 2022 / Revised Mar. 7, 2022 / Accepted Mar. 21, 2022)