IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁘ Impact Factor 8.102 ⁘ Peer-reviewed / Refereed journal ⁘ Vol. 12, Issue 5, May 2023

DOI: 10.17148/IJARCCE.2023.12537

Medicinal Plants Identification using Convolution Neural Network

Mrs.J.L.B.Sharmila M.E[1] , Anisha.S[2], Angel Sneha.A[3] , Preethi Salo.J[4]

Department of Computer Science, DMI College of Engineering, Chennai – 600 123 [1-4]

Abstract: From Vedic times plants have been used as a source of medicine in ayurveda. In the preparation of ayurvedic medicine, identification of correct plant is the most important step, which has been done manually. Due to demand of mass production, Identification of these plants automatically is important. In this project we have been implement a technique for medicinal plant identification using random forest algorithm, an ensemble supervise machine learning algorithm based on color, texture and geometrical features then reduced feature vectors are inputted into the classification model. Convolution Neural Network (CNN) is used for classification and identifying the animal class.

Keywords – CNN – Convolution Neural Network

INTRODUCTION

Plants are of central importance to natural resource conservation. Plant species identification provides significance information about the categorization of plants and its characteristics. Manual interpretation is not precise since it involves individual's visual perception. Sampling and capturing digital leaf images are convenient which involves texture features that help in determining a specific pattern. The most important feature to distinguish among plant species are venation and shape of a leaf. As information technology is progressing rapidly, techniques like image processing, pattern recognition and so on are used for the identification of plants on basis of leaf shape description and venation which is the key concept in the identification process. Varying characteristics of leaves are difficult to be recorded over time. hence it is necessary to create a dataset as a reference to be used for a comparable analysis. Leaves are used in most of the plant identification methodologies due to their attractive properties and availability throughout the year. modern medicine is massively produced for medical treatment but many first world countries are now opting for traditional medicine due to the limitation of synthetic drugs in controlling and curing chronic diseases (who 1999). Traditional medicines are used extensively in the pharmaceutical industry, as claimed in (karami et al. 2017), where a quarter of the globally prescribed drug are extracted from medicinal plants. this is due to the benefts of medicinal plants that offer substantially lower adverse reactions and more cost effective as compared to synthetic drugs (lulekal et al. 2008). Furthermore, bioactive compounds such as phenolics, carotenoids, anthocyanins and tocopherols that can be extracted from medicinal plants (altemimi et al. 2017) serve as antioxidants, anti-allergenic, anti-inflammatory, antibacterial and also anti-hepatotoxic. nonetheless, the task of identifying medicinal plants manually is complicated and time consuming, similar to other plant recognition and this is due to the availability of expert opinions (sladojevic et al. 2016; singh and misra 2017; wäldchen et al. 2018). Inspired by these problems, researchers introduced numerous automatic plants or leaf recognition systems, where most of them utilized machine learning approaches. Machine learning is a branch of artificial intelligence which allows machines to identify patterns and make decisions with minimal human intervention. Machine learning has been used to obtain impressive recognition, prediction and filtration results on many problems such as medical diagnosis, financial analysis, predictive maintenance and image recognition. Currently, there are various types of machine learning algorithms and these algorithms can be classified into three categories, namely supervised, unsupervised and semi supervised. in supervised learning, the algorithm makes decisions based on the labeled input data, where the training process continues until the classifier able to achieve the highest accuracy (el mohadab et al. 2018). there are also machine learning algorithms that can be trained without labeled data and these algorithms are categorized under unsupervised learning (el mohadab et al. 2018). in some cases, there is a need for semi-supervised learning, where the algorithms are trained using both labeled and unlabelled data (zhu and goldberg 2009).

1. LITERATURE SURVEY

A leaf recognition algorithm for plant classification using probabilistic neural network, S.G.Wu, F.S.Bao, E.Y.Xu, Y.-X.Wang, Y.-F.Chang and Q.-L. Xiang, In this paper, we employ Probabilistic Neural Network (PNN) with *image*

DOI: 10.17148/IJARCCE.2023.12537

and data processing techniques to implement a general purpose automated leaf recognition for plant classification.The PNN is trained by 1800 leaves to classify 32 kinds of plants.

Automatic plant identification from photographs, B. Yanikoglu · E. Aptoula · C. Tirkaz . This paper presents an automatic plant identification system from digital photographs. The system is tested on a dataset of nine different plant species.The system is trained on a dataset of digital photographs of plants and uses a set of features to identify plant species.

Plant Leaf Recognition Using Texture Features and Semi-Supervised Spherical K-means Clustering, Shadi Alamoudi, Xia Hong, Hong Wei. The method uses texture features such as Gabor Filters, Local Binary Patterns, and Color Moments, to extract features from the leaf images. The spherical K-means clustering algorithm is then used to cluster the extracted features and classify the plant leaf images. The proposed method was tested on a dataset of 100 plant species.

Machine learning in medicinal plants recognition, Kalananthni Pushpanathan1, Marsyita Hanaf1, Syamsiah Mashohor1, Wan Fazilah Fazlil Ilahi2. This paper provides an overview of the application of machine learning techniques in medicinal plants recognition. It focuses on the challenges and recent advances in the field, as well as existing methods and algorithms used to identify medicinal plants.

A Leaf Recognition Algorithm for Plant Classification Using Probabilistic Neural Networks, Stephen Gang Wu1, Forrest Sheng Bao2, Eric You Xu3, Yu-Xuan Wang4, Yi-Fan Chang5 and Qiao-Liang Xiang4. This paper presents a leaf recognition algorithm to classify plants using probabilistic neural networks.

The authors use a combination of morphological and texture features to represent a leaf image

Royetal(2014) studied seed and seedling morphology of Diploknema butyracea. Diploknema was reported from Jumpui hills of Tripura and was a multi purpose plant of the sub-Himalayan tract. Its how edphaneroepigeal type of germination and leaves had hypostomatic with anomocytic stomata. Seed and seedling morphology of Aquilaria malaccensis Lamk, a threatened species, in Tripurahad been studied from regeneration and conservation point of view by Roy and Datta(2014). This study had observed that Aquilaria had high seedling production and regeneration capacity with phaneroepigeal reserve type of germination.

Roy and Datta(2014) conducted an investigation for phonetic analysis of 8 species of sub-tribe Cassiineae (Sennatora, Sennasophera, Senna occidentalis, Sennasiamea, Cassiafistula, Sennaalata, Cassiarenigera, Cassiajavanicassp.nodosa) with respect to seedling morphology in Tripura. Alltaxa belongs to family Leguminosae and all had phaneroepigeal foliaceous type of germination. Artificial key had been prepared for easier identification of all investigated taxa.

Paria and Sanyal(2015) documented 25 taxa under 18 genera of familyLeguminosae(Acaciaauriculiformis,Atylosiascarabaeoides,Bauhiniapurpurea,Buteamonosperma,Calliandraumbrosa,Cassiaalata,Cassiafistula,Cassiasiamea,Cassiasophera,Cassiatora,Crotalariapallid,Dalbergiasissoo,Delonixregia,Leucaenaleucocephala,Millettiaovalifolia,Mimosapudica,Peltophorumpterocarpum,Pithecellobiumdulce,Pongamiapinnata,Samaneasaman,Saracaasoca,Sesbaniacannabina,Sesbaniagrandiflora,SesbaniasesbanandTephrosiapurpurea.) from Salt Lake City in West Bengal. To determine inter-relationships among the investigated taxa they had also done cluster analysis and principal component analysis.

Jadhav and Chavan(2015) had done a comparative account of seedling morphology of three Luffa species(Luffaacutangulavar. amara,L.acutangula and L.cylindrica.). Sivada setal(2015) recorded seedling stage of Lagerstroemia speciosa from family Lythraceae upto sixth leaf stage. Singh(2015) recorded fifteen dicotweeds in their juvenile stage(Achyranthesaspera, Alternantheraparonychioides,Amaranthusviridis,Argemonemexicana,Chenopodiumalbum,Digeramuricata,Euphorbia hirta,Lathyrusaphaca,Medicagopolymorpha,Melilotusindica,Oldenlandiaaspera,Oxaliscorniculata, Parthenium hysterophorus, Solanum nigrum and Spergulafallax).

In 2015, Singh investigated Oroxylumindicum seedling and talked about its taxonomical importance. Bose and Paria(2015a,2015b) had observed seedling morphology of Cheilocostusspeciosus(Costaceae) and Hyphaenethebaica(Arecaceae) and pointed out importance of seedling morphology in taxonomy. According to Sanyal and Paria(2015), seed and seedling traits play critical role in identification of species. Meena and Datta(2015) studied

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁜ Impact Factor 8.102 ⁜ Peer-reviewed / Refereed journal ⁜ Vol. 12, Issue 5, May 2023
DOI: 10.17148/IJARCCE.2023.12537

seedling and their taxonomic importance of some species of Acacia (A.niloticasubsp.indica ,A.senegal, A.raddiana and A.catechu) Seedling characters upto 3rd to 4th leaf stages had been recorded.

Kumar and Chauhan(2016) studied seedling morphology of Wrightiaar bore and W.tinctoria. Both species belongs to family Apocynaceae and were medicinally important and were endangered in the Vindhyan region. Srivastava and Kumar(2016) studied seedling of Sesbania. Yogeeshaetal(2016) studied seeds of threatened under-utilized Baccaurea courtallensis of western ghat. Seeds of Podostemaceaeare very small and abundant and germinate quickly in light and water. Seed features of Podostemaceae and their survival had been investigated by Uniyal(2016). Nakar and Jadeja(2016) studied 11 taxa(9 trees and 2 under shrubs) from Girnar Reserve Forest(Aeglemarmelos ,Albizialebbeck, Bombaxceiba, Cassiaauriculate, Cassiaoccidentalis, Cassia siamea, Ceibapentandra, Delonix regia, Leucaenaleucocephala, Peltophorumpterocarpum, Sterculiaurens) in Gujrat.

Sanyal(2017) had studied 139 taxa in their juvenile stage of Taki, North 24 Parganas in West Bengal. Using seedling character sartificial key had been prepared for identification of taxa. 5 species of Magnolia(M.campbellii, M.cathcartii, M.champaca, M.doltsopa, M.lanuginosa) had been investigated on the basis of

Seedling morphology by Boseetal(2017). Paria and Bose(2017) had stressed on seedling morphology and its potential in taxonomic studies in Indian flora. Ingole and Adikane(2017) had studied seed morphology(shape, size, texture, surface, hilum shape and position) and seed coat anatomy of eleven medicinal important plants of family Acanthaceae.

2. PROPOSED SYSTEM

The image processing techniques have been established to optimize the footprints, input image is converted into greyscale, Edge detection on the image.

All the images in the dataset are read, processed, and feature extracted, raw data is loaded for classification of input image.

This project proposed a Fuzzy C-means response, for extracting texture features and preserves texture features of an image in frequencies.

Selective scale and orientation filter is applied on input image to acquire texture features.

And Segmentation requires separating the image from the background for efficient classification.

Next step is extracting templates of the footprints.

In template matching process along with template updating is specified.

CNN classifier is used for identifying the medicinal plant.

Since, our proposed method falls on the classification of multiple classes, the binary CNN model has been extended to multinomial logistic regression.

Through a combination of binary CNN, multiple groups are compared by the multinomial logit .

3.1. Advantages of Proposed System:

The purpose of this work is to improve our previously proposed prediction framework through alternative Plant mapping and feature engineering approaches, and provide an open-source implementation.
This work helps the law enforcement agencies to predict and detect Plant in Indiausing foot prints with improved accuracy and thus reduces the time rate.

3. DESIGN & IMPLEMENTATION

4.1. Data Collection:

The Dataset used for this work contains 60 classes of medicinal plant where 20 images in each class.

70% of the images is used as train data and 30% of the images is used as test data.

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁜ Impact Factor 8.102 ⁜ Peer-reviewed / Refereed journal ⁜ Vol. 12, Issue 5, May 2023
DOI: 10.17148/IJARCCE.2023.12537

4.2. Data Pre-processing:

Re-processing plant leaves images are converted into gray-scale [13]. Gray-scale image is a image consists of binary

contents in the form of 0 and 1 pixels of the initial rgb image.

Gray-scale image consists of image pixel is a single sample representing only small amount of light, it carries only intensity information between (0 to 1).

The converted gray scale for further processing, it should be further reduced in information which includes edge detection.

4.3. Feature Extraction Module:

Here we choose Gabor filters for the purpose of feature extraction. Gabor filters effectively preserves the texture characteristics of an image pattern in frequency domain. By applying the selective scale and orientation gabor filter on an image where, the texture analysis is accomplished.Initially the image are segmented before extracting desired feature

4.4. Classification Module:

Classification: After processing and feature extraction we have to determine the animal class by comparing the input image with trained data, trained data consists of 80 percent samples, probabilistic neural network is used for footprint classification.

4.5. Saving the Trained Model:

Once you're confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into a .h5 or .pkl file using a library like pickle .Make sure you have pickle installed in your environment. Next, let's import the module and dump the model into.pkl file.

4. CONCLUSION

This research highlights the enormous potential of picture classification algorithms and how they can be utilized to outperform humans in a range of classification tasks. With advances being made daily in the domains of picture classification and computer vision, this suggested method, if implemented on a wider scale, has the potential to dramatically alter the way traditional medicine such as Ayurveda, Unani, and others is performed in the nation. One of the primary disadvantages of traditional medicine that is impeding its popularity and expansion is a lack of information about the requisite plants/plant extracts among the urban people. This initiative may assist in overcoming this disadvantage by offering an effective and user-friendly interface for identifying and using these plants. Even though the suggested system is fully functional in its current form, it cannot be used as a real-time application without a few critical enhancements: To begin, a beautiful and simple-to-use user interface must be built so that the system can be used without difficulty and provide the intended outcomes. Additionally, if networking capabilities are included, the user will be able to access enormous web resources to learn more about the plant specimen in question, rather than relying on pre-loaded data. Moreover, the CNN method may be improved by hyperparameter tweaking, data redesign, and model optimization.

ACKNOWLEDGEMENTS

I am immensely pleased in taking up this opportunity to thank the LORD ALMIGHTY for showering this unlimited blessing upon us.
I take this opportunity to express my gratitude to our Founder and Chairman Rev.Fr.Dr.J.E.Arulraj, Our Correspondent Rev.Sr.M.K.Teresa, and our Administrator Rev.Sr.P.Pradeeba, for for allowing us to take over this project.
I thank our principal Dr.N.Azhagesan,M,Tech.,Ph.D, who has always served us an inspiration for me to carry out my responsibilities also providing comfort zone for doing this project work.
I wish to express my sincere thanks to Dr.D.R.Denslin Brabin, M.E.,Ph.D, Head of the Department and Mr.L.Jimson,M.E.,(Ph.D), Project Coordinator for their scintillating discussion and encouragement towards our project.
I express my deep sense of gratitude and thanks to my esteemed Supervisor, Mrs.J.L.B.SHARMILA M.E, for constant guidance and co-operation during the project work.

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁞ Impact Factor 8.102 ⁞ Peer-reviewed / Refereed journal ⁞ Vol. 12, Issue 5, May 2023
DOI: 10.17148/IJARCCE.2023.12537

It is a pleasure to acknowledge my indebtedness to all the Teaching and Non-Teaching staff of Department Computer Science and Engineering who aided us successfully to bring our project as an effective one.
Further thanks to our parents, our family members and friends for their moral support.

REFERENCES

[1] Manojkumar P., Surya C. M., and Varun P. Gopi, "Identification of Ayurvedic Medicinal Plants by Image Processing of Leaf Samples", 2017 Third International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN), pp 978- 1- 5386-1931-5.

[2] Mr. K.Nithiyanandhan and Prof.T.Bhaskara Reddy, "Analysis of the Medicinal Leaves by using Image Processing Techniques and ANN", Vol 8, No. 5, ISSN No. 0976-5697, MayJune 2017.

[3] Adams Begue, VenithaKowlessur, FawziMahomoodally, Upasana Singh and Sameerchand, "Automatic Recognition of Medicinal Plants using Machine Learning Techniques", International Journal of Advanced Computer Science and Applications, Vol. 8, No. 4, 2017.

[4] H. X. Kan, L. Jin, and F. L. Zhou," Classification of Medicinal Plant Leaf Image Based on Multi-Feature Extraction", Pattern Recognition and Image Analysis, Vol. 27, No. 3, 2017, pp. 581–587, 1054-6618. © Pleiades Publishing, Ltd.

[5] Riddhi H. Shaparia, Dr. Narendra M. Patel and Prof. Zankhana H. Shah," Flower Classification using Texture and Color Features", International Conference on Research and Innovations in Science, Engineering &Technology, Volume 2, 2017, Pages 113–118.

[6] Marco Seeland, Michael Rzanny, NedalAlaqraa, Jana Wa ̈ldchen, Patrick Ma ̈der, "Plant species classification using flower images—A comparative study of local feature representations", PLOS ONE | DOI:10.1371/journal.pone.0170629 February 24, 2017.

[7] Pradeepkumar Choudhary, Rahul Khandekar, AakashBorkar, and PunitChotaliya, "Image processing algorithm for fruit identification", International Research Journal of Engineering and Technology (IRJET), Vol 4 Issue 3, e-ISSN: 2395 -0056, p-ISSN: 2395- 0072, Mar -2017.
[8] D Venkataraman and Mangayarkarasi N, "Computer Vision Based Feature Extraction of Leaves for Identification of Medicinal Values of Plants", IEEE International Conference on Computational Intelligence and Computing Research, 978-1-5090-0612-0/16/$31.00 ©2016 IEE.

[9] R. Haining, ``Mapping and analysing crime data: Lessons from research and practice," Int. J. Geogr. Inf. Sci., vol. 16, no. 5, pp. 203507, 2002.

[10] S. Chainey, L. Tompson, and S. Uhlig, ``The utility of hotspot mapping for predicting spatial patterns of crime," Secur. J., vol. 21, nos. 12, pp. 428, Feb. 2008.

[11] S. Chainey and J. Ratcliffe, ``GIS and crime mapping," Soc. Sci. Comput. Rev., vol. 25, no. 2, pp. 279282, 2005.

[12] L. Lin,W. J. Liu, andW.W. Liao, ``Comparison of random forest algorithm and space-time kernel density mapping for crime hotspot prediction," Prog. Geogr., vol. 37, no. 6, pp. 761771, 2018.

[13] C. L. X. Liu, S. H. Zhou, and C. Jiang, ``Spatial heterogeneity of microspatial factors' effects on street robberies: A case study of DP Peninsula," Geograph. Res., vol. 36, no. 12, pp. 24922504, 2017.

[14] M. I. Jordan and T. M. Mitchell, ``Machine learning: Trends, perspectives, and prospects," Science, vol. 349, no. 6245, pp. 255260, Jul. 2015.

[15] X. Zhao and J. Tang, ``Modeling temporal-spatial correlations for crime prediction," in Proc. Int. Conf. Inf. Knowl. Manag. Proc., vol. F1318, 2017, pp. 497506.

[16] A. Babakura, M. N. Sulaiman, and M. A. Yusuf, ``Improved method of classication algorithms for crime prediction," in Proc. Int. Symp. Biometrics Secur. Technol. (ISBAST), 2015, pp. 250255.

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁙ Impact Factor 8.102 ⁙ Peer-reviewed / Refereed journal ⁙ Vol. 12, Issue 5, May 2023
DOI: 10.17148/IJARCCE.2023.12537

[17] Q. Zhang, P. Yuan, Q. Zhou, and Z. Yang, ``Mixed spatial-temporal characteristics based crime hot spots prediction," in Proc. IEEE 20th Int. Conf. Comput. Supported Cooperat. Work Design (CSCWD), May 2016, pp. 97101.

[18] A. R. Dandekar and M. S. Nimbarte, ``Verication of family relation from parents and child facial images," in Proc. Int. Conf. Power, Autom. Commun. (INPAC), 2014, pp. 157162.

[19] G. R. Nitta, B. Y. Rao, T. Sravani, N. Ramakrishiah, and M. BalaAnand, ``LASSO-based feature selection and Naïve Bayes classier for crime prediction and its type," Serv. Oriented Comput. Appl., vol. 13, no. 3, pp. 187197, 2019.

[20] H. Tyralis and G. Papacharalampous, ``Variable selection in time series forecasting using random forests," Algorithms, vol. 10, no. 4, p. 114, Oct. 2017.

[21] K. K. Kandaswamy, K.-C. Chou, T. Martinetz, S. Möller, P. N. Suganthan, S. Sridharan, and G. Pugalenthi, ``AFP-pred: A random forest approach for predicting antifreeze proteins from sequence-derived properties," J. Theor. Biol., vol. 270, no. 1, pp. 5662, Feb. 2011.

[22] V. F. Rodriguez-Galiano, B. Ghimire, J. Rogan, M. Chica-Olmo, and J. P. Rigol-Sanchez, ``An assessment of the effectiveness of a random forest classier for land-cover classication," ISPRS J. Photogramm. Remote Sens., vol. 67, pp. 93104, Jan. 2012.

[23] L. Lin, J. Jiakai, S. Guangwen, L. Weiwei, Y. Hongjie1, and L. Wenjuan, ``Hotspot prediction of public property crime based on spatial differentiation of crime and built environment," J. Geo-Inf. Sci., vol. 21, no. 11, pp. 16551668, 2019.

[24] Z. Jun and H. Wenbo, ``Recent advances in Bayesian machine learning," J. Comput. Res. Develop., vol. 52, no. 1, pp. 1626, 2015.
[25] J. T. Huang, J. Li, and Y. Gong, ``An analysis of convolutional neural networks for speech recognition," in Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP), South Brisbane, QLD, Australia, Apr. 2015, pp. 49894993.

[26] Z. Feiyan, J. Linpeng, and D. Jun, ``Review of convolutional neural network," Chin. J. Comput., vol. 40, no. 6, pp. 12291251, 2017.

[27] Y. Yang, J. Dong, X. Sun, E. Lima, Q. Mu, and X.Wang, ``A CFCC-LSTM model for sea surface temperature prediction," IEEE Geosci. Remote Sens. Lett., vol. 15, no. 2, pp. 207211, Feb. 2018.

[28] X. Hong, R. Lin, C. Yang, N. Zeng, C. Cai, J. Gou, and J. Yang, ``Predicting Alzheimer's disease using LSTM," IEEE Access, vol. 7, pp. 8089380901, 2019.

[29] L. Mou, P. Zhao, and Y. Chen, ``Short-term trafc ow prediction: A long short-term memory model enhanced by temporal information," in Proc. 19th COTA Int. Conf. Transp. Prof. CICTP Transp. China-Connect.World, 2019, pp. 24112422.

[30] L. E. Cohen and M. Felson, ``Social change and crime rate trends:Aroutine activity approach," Amer. Sociol. Rev., vol. 44, no. 4, p. 588, Aug. 1979.

[31] G. Gudjonsson, ``The reasoning criminal. Rational choice perspectives on offending," Behav. Res. Therapy, vol. 26, no. 3, pp. 246287, 1988.

[32] P. Brantingham and P. Brantingham, ``Criminality of placeCrime generators and crime attractors," Eur. J. Crim. Policy Res., vol. 3, no. 3, pp. 526, 1995.

[33] Enhancing Urban Safety and Security. Global Report on Human Settlements 2007, UN-Habitat, Nairobi, Kenya, 2007.

[34] G. Owusu, C. Wrigley-Asante, M. Oteng-Ababio, and A. Y. Owusu, ``Crime prevention through environmental design (CPTED) and built environmental manifestations in Accra and Kumasi, Ghana," Crime Prevention Community Saf., vol. 17, no. 4, pp. 249269, Nov. 2015.

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⵋ Impact Factor 8.102 ⵋ Peer-reviewed / Refereed journal ⵋ Vol. 12, Issue 5, May 2023
DOI: 10.17148/IJARCCE.2023.12537

[35] Y. Wenhao and A. Tinghua, ``The visualization and analysis of POI features under network space supported by kernel density estimation," Acta Geodaetica et Cartographica Sinica, vol. 44, no. 1, pp. 8290, 2015.

[36] G. Song, L. Xiao, S. Zhou, D. Long, S. Zhou, and K. Liu, ``Impact of residents' routine activities on the spatial-temporal pattern of theft from person," Acta Geography Sinica, vol. 72, no. 2, pp. 356367, 2017.

[37] L. Lin, D. Fang-Ye, X. Lu-Zi, S. Guang-Wen, and J. C. L. Kai, ``The density of various road typesand larceny rate: An empirical analysis of ZG city," Hum. Geeography, vol. 32, no. 6, pp. 3239, 2017.

[38] C. Xu, L. Liu, and S. H. Zhou, ``The comparison of predictive accuracy of crime hotspot density maps with the consideration of the near similarity: A case study of robberies at DP Peninsula," Scientia Geographica Sinica, vol. 36, no. 1, pp. 5562,2016.

[39] G. Rosser, T. Davies, K. J. Bowers, S. D. Johnson, and T. Cheng, ``Predictive crime mapping: Arbitrary grids or street networks," J. Quantum Criminol., vol. 33, no. 3, pp. 569594, 2017.

[40] D. Grifth, Multivariate Statistical Analysis for Geographers. Upper Saddle River, NJ, USA: Prentice-Hall, 1997.

[41] A. Rummens,W. Hardyns, and L. Pauwels, ``The use of predictive analysis in spatiotemporal crime forecasting: Building and testing a model in an urban context," Appl. Geography, vol. 86, pp. 255261, Sep. 2017.

[42] S. Favarin, ``This must be the place (to commit a crime). Testing the law of crime concentration in Milan, Italy," Eur. J. Criminol., vol. 15, no. 6, pp. 702729, Nov. 2018.

[43] M. Felson and E. Poulsen, ``Simple indicators of crime by time of day," Int. J. Forecasting, vol. 19, no. 4, pp. 595601, Oct. 2003.

[44] A. Sagovsky and S. D. Johnson, ``When does victimisation occur?" Australia. New Zealand J. Criminol., vol. 40, no. 1, pp. 216, 2007.