Deep Spatio-Temporal Learning for Urban Traffic Congestion Prediction

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Abstract: These so-called "Internet of Things" (IoT) devices collect the data that varies with time and place, such as weather, traffic, and health monitors. This is referred to as spatio-temporal big data (STBD). Traditional systems struggle with large, complex sets of information and cannot quickly analyze the data. This article examines the application of the current big data technologies for managing, processing and analyzing STBD from four layers perspective. Processing is parallelized in the Data Processing Layer, built on Hadoop and Spark, and stored in the Data Management Layer, built on the scalable MongoDB. In the Data Analysis Layer, AI models such as CNN2D are applied to forecast phenomena such as traffic jams. Finally, the Cloud Native Layer is able to leverage these technologies on cloud platforms, ensuring that they can be scaled up and used by all. The CNN2D model got a R^2 score of 85% on a collection of over 50,000 records about traffic jams on roads. Models using hybrid with CNN+BILSTM and CNN+BI-GRU showed improved performance with the R^2 of 90% and 88%, respectively. These results show that this method can be used to make accurate predictions and analyses. They are useful for applications involving the IoT that generate spatiotemporal data, such as in traffic management, healthcare, and others.

*"**Index Terms -** Spatio-Temporal Big Data (STBD), Big Data Analytics, Resource Management, Deep Learning Models (CNN2D, CNN+BILSTM, CNN+BI-GRU), Cloud-Based Processing, Traffic Congestion Prediction".*

1. INTRODUCTION

With the rapid development of the Internet, IoT, GIS and data collection, the STBD has developed significantly over the years. Putting together spatiotemporal data with big data analytics has opened up new possibilities in many areas. This has greatly increased the amount and variety of data, filling in gaps in standard databases with detailed, multidimensional data. As a result, researchers with diverse backgrounds are now able to collaborate on projects such as smart transportation systems, urban planning and environmental monitoring, etc. [1, 2].

One of the best parts of STBD is the fact that it allows people to document how things and events change and interact over time. However, it is constantly evolving and is difficult to manage, process and analyze data. Geographical and temporal aspects change constantly, making it difficult to find effective indexing, retrieval and computing methods. The size and velocity of STBD make it unsuitable for traditional databases, thus requiring special tools. Different types of computing platforms and spatiotemporal indexing methods, such as multi-source data cubes, have been created to deal with these problems [3, 4].

Concurrently, the capacity and performance of computers have advanced, thereby altering the processing of large data sets. Today, STBD analytics is a lot more useful thanks to the cloud computing, parallel processing and high-performance computer frameworks. These improvements enable computers to operate on a large scale and in real time. This enables various scenarios, such as traffic prediction, disaster response, smart city planning, and more, to be more efficient. GISs are using strong and advanced computer techniques these days, making them more adaptable and useful. To facilitate the storage, retrieval, and analysis of large STBD data systems, the underlying data frameworks used for the storage and retrieval are of the spread out indexing and time-series variety [5, 6].

An improved ability to make more accurate predictions, make decisions in real time and link to AI models is still a challenge for STBD analytics. DL methods to improve STBD-driven insights were looked into by researchers. CNN, LSTM, and hybrid models have been demonstrated to have the ability to learn spatiotemporal features. This has been beneficial in the field of prediction, such as healthcare, transportation, and land management areas [6, 7].

Overall, the rapid advancement of STBD analytics demonstrates the significance of continuing to find innovative methods of managing data, processing it, and creating applications. Taking care of these issues will make STBD more important in many real-life situations as study gets better [7].

2. RELATED WORK

Based on the spatiotemporal data, Yu et al. proposed a smart city road running and maintenance intelligent system named RIOMS. Their approach uses both ML and big data analytics to make it easier to keep an eye on infrastructure, guess how roads will be in the future, and plan maintenance. Historical and real-time road data are useful to urban planners and can be used to make better decisions, thereby reducing the operational costs and improving the safety of the road.

Ale et al. presented a Bayesian learning paradigm to plan the mobile edge computing resources in smart cities to consider both space and time. The principal purpose of their research is to determine a way of doing most effective use of computer resources by forecasting changes in work across time and space. The system applies the Bayesian learning algorithm to dynamically distribute edge-computing resources as per the changes in demand. This allows smart city applications to be more efficient and reduces latency. Cloud-edge integration is a lot better due to this architecture that ensures that real-time applications such as self-driving cars and IoT networks can deal with data and respond quickly [9].

Shen et al. came up with a new way to use Google Earth Engine to find out how area environmental problems change over time and space. They study using big data obtained from remote sensing to monitor changes in the environment. This will enable us to understand more about how ecosystems evolve. Their approach constructs a spatial data analysis framework at a global scale and assists policy makers and academics in identifying high-risk ecological regions that can be used to inform long-term land use planning. According to this research, using satellite images in combination with large data techniques will be more effective in protecting the environment [10].

Chergui and Kechadi began to examine the challenge of using big data analytics for crop management, and developed a complete framework that leverages spatiotemporal data to enable a more efficient farming system. Their research demonstrates the potential of the modern application of data analytics to aid farmers in decision making by monitoring factors such as crop health, soil conditions, and climate change. Through ML algorithms and the processing of big data, they can provide farmers with useful information, which can help them to make more profits and decrease losses. In precision agriculture, AI-driven analytics are becoming more important, especially when it comes to making sure there is enough food and getting the most accurate output predictions [11].

To prevent pandemics such as COVID-19, Wang et al. have developed a disease control platform, called WDCIP, which is based on AI and provides time-based and place-based management to control disease. The program utilizes real-time spatial data from numerous sources that include weather, transportation and health information to determine how infectious diseases will be spread. WDCIP provides decision makers with valuable data to act fast with, as well as ML and spatiotemporal data. This research shows that big data technology can help public health by preventing and controlling epidemics before they happen [12].

Firatli et al. applied remote sensing and big data analysis techniques for the monitoring of the changes over time and space in the environment of natural lakes in Turkey. They study water level change, pollution level and seasonal changes. This provides us with valuable information for managing the environment. The study leverages satellite imagery and predictive modelling to illustrate the impact of climate change and human activities on freshwater ecosystems [13]. This is beneficial for the long-term management of water resources.

Sun et al. looked into how big data analytics could be used to keep an eye on old trees, which is an important part of protecting the environment. They conduct both retrospective and on-the-spot analysis of trees' health, disease, and future threats such as urbanization or deforestation through their study. Their system, based on innovative data processing techniques, ensures protection of the biodiversity along with the preservation of old trees. Most of their research is focused on the interaction of old data and new technology for the purpose of monitoring the world [14].

In their research on time-series land cover mapping and urban expansion study, Ding et al. investigated the study with remote sensing big data and OpenStreetMap data. They are primarily concerned with understanding and identifying patterns of landscape change over time in urban environments, along with the development of infrastructure. Their research is useful for urban planners and policymakers, as it integrates information on both space and time with AI techniques for sorting items into meaningful clusters. The outcomes have been used to contribute to sustainable urban development by predicting future urban development and analyzing the influence of human activities on the changes in land cover over time [15].

All these pieces demonstrate the potential strengths of spatio-temporal big data analytics in numerous areas. Smart towns can utilize the computer resources optimally, and techniques such as RIOMS contribute to maintaining infrastructure in good condition. The study of ecological threats, changes in natural lake characteristics and land use change over time and space is a part of environmental management for planning measures that will protect the environment and ensure its sustainability. In the farming sector, big data analytics can help to monitor crops with greater accuracy, optimising their growth and maximizing resource utilization. Healthcare systems, such as WDCIP, powered by AI, present novel solutions to combat diseases and manage pandemics. Finally, big data tools keep historical sites alive by combining old and new data insights to ensure preservation of old trees.

As spatiotemporal big data changes, it will be important to handle its complexity by combining high-performance computing tools, ML models, and cloud-native architectures. Future research needs to be directed toward the development of improved methods of data processing, more accurate predictive models, and more scalable methods. With the ability to solve data merging, computing efficiency, and real-time processing problems, the next generation of spatio-temporal big data applications will be able to find new applications in many areas. This demonstrates that it is crucial to obtain knowledge about this issue in various disciplines.

3. MATERIALS AND METHODS

The proposed system is able to manage, process, and analyze STBD collected from IoT devices in healthcare, traffic control and environmental monitoring in a fast and effective manner. It is designed in four layers, including a scalable storage layer based on MongoDB, a data processing layer based on Hadoop and Spark for processing data in parallel, and an AI layer for making predictions, such as CNN2D. CNN+BILSTM and CNN+BI-GRU are two hybrid types of model that can make more accurate predictions [6]. Cloud-native approach is scalable and easily accessible using cloud platforms for real-time processing [7]. The approach enhances the performance of STBD analysis with over 50,000 road traffic congestion records. This lets accurate predictions of congestion be made and decisions to be made in real time [5].

This way makes applications that use a lot of data better for smart cities and smart transportation systems [4]. Comparable STBD frameworks had been successfully used in visitor planning, disaster management, and several interdisciplinary fields requiring large-scale spatiotemporal assessments [16,20].

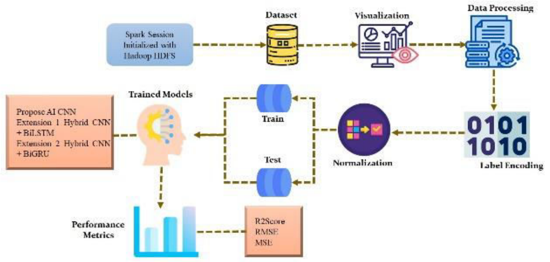

Fig.1 Proposed Deep Spatio-Temporal Learning Architecture

AI CNN models are used in this system to look at large amounts of spatiotemporal data. Hadoop HDFS starts a Spark session to work on the information. Data processing, data labelling, visualisation and data standardisation have been completed. AI CNN, Hybrid CNN+BILSTM, and Hybrid CNN+BIGRU are some of the models that are taught and tested. The models are judged by performance measures such as R2Score, RMSE and MSE. This approach allows the study of very large spatiotemporal data for various applications in an easy way.

A) Dataset Collection:

The traffic_data file contains useful information about traffic jams, such as where they are, when they occur, and the weather conditions at the time. This data is used to process quickly, and to achieve this, a Spark connection is made first. The information is then read and stored in the HDFS file system. This makes sure that the system can grow and handle errors. After loading the data, the data structure, data columns and basic statistics of the data are checked. This procedure allows for exploration of the distribution of data, filling in of missing values, and choosing of the most suitable features for predictive modelling. After cleaning, it is input into the AI system that can aid in better prediction and management of traffic flow.

B) Pre-processing:

The data is given a better quality; more accurate estimates are obtained from the pre-processing. It has feature scaling to increase model performance, label encoding to convert categorical data to number data , data processing for missing values and pattern recognition .

a) Visualization: Visualization helps us understand the below factors for traffic jams: It helps us to produce graphs and charts showing traffic flow at different locations and different time periods. Heatmaps, bar charts and line graphs are used to show the spatial and temporal distribution including peak traffic times [19]. Results are used to determine problem areas and the results of traffic control. Data visualization approaches allow easy understanding of data and assist in decision making in traffic control and predictive models.

b) Data Processing: The data processing takes care of cleaning the traffic data from unprocessed data and then organizing the data before examined. At this stage, default values are placed in any null cells and any unnecessary information is removed, date-time data is transformed into numeric data (e.g. year, month, hour, etc.). Also, we can work with non-standard data formats to standardise these. By processing the data correctly to get the quality of the data, they can be assured that the ML models have accurate and dependable information that would aid them in making accurate predictions of traffic jams.

c) Label Encoding: A method used to encode common data like the type of road or the weather conditions to numbers is known as Label Encoding. It is a basic approach for ML models requiring numerical values in order to function correctly. In order to prevent errors during model training, each group is given a different number. Label encoding is one of the techniques that can successfully add category information to the prediction models. This enables them to quickly analyze the traffic patterns in space and time, and accurately predict congestion.

d) Normalization: Normalization is a process that transforms data to the normal range to make the model more stable and efficient. This avoids the super-important traffic from being more important than the little-important weather. Many people employ Z Score Normalization and Min-Max Scale. Normalization reduces bias in the model predictions, and improves convergence during training, thus making it easier to identify and predict traffic bottlenecks.

C) Training and testing

We divide the information to two sets: training and testing. This is so a good model can be constructed to predict traffic congestion. The data is usually split into 80% for the training set which is used to train the artificial intelligence models like CNN2D, CNN+BILSTM and CNN+BI-GRU. This lets them train their ability to deal with crowding in space-time. The remaining 20% is reserved for a test set to evaluate the model's ability to make predictions that it has not encountered before. This split avoids over-fitting, and assures that the model behaves correctly in real life traffic scenarios. The technology is able to break down the data and accurately assess traffic jams to provide urban mobility planning or transportation management.

D) Algorithms

AI CNN (Convolutional Neural Network): CNN is familiar with analyzing traffic data in both time and space and is able to detect spatial patterns to forecast traffic jams. It also simplifies computations on large data sets [1, 5] without sacrificing accuracy. CNN is helpful to predict traffic, improves the management of intelligent transportation system [6].

$$Y_{i,j,k} = \sum_m \sum_n W_{m,n,k} \,.\, X_{i+m,j+n} + b_k (1)$$

Hybrid CNN + BiLSTM: CNN and BiLSTM are used together, making extraction of the feature in both space and time easier and thus more accurate in predicting traffic jams. BiLSTM can capture the long-term relationship of a sequence of traffic data, thus producing more accurate prediction and reducing the incidence of errors in traffic change scenarios [1, 6]. Standalone CNNs don't do as well as this model [5].

$$\overrightarrow{h_t} = \sigma(W_f X_t + U_f \overrightarrow{h_{t-1}} + b_f (2)$$

$$\overleftarrow{h_t} = \sigma(W_b X_t + U_b \overleftarrow{h_{t+1}} + b_b$$

Hybrid CNN + BiGRU: The best way to extract spatiotemporal features while lowering the amount of work that needs to be done is with CNN and BiGRU. GRU performs well with sequential data which enables it to make fast and accurate predictions of congestion [5]. This hybrid approach optimizes traffic prediction in real-time applications by delivering the most accurate predictions in the shortest time possible [6]. Recent improvements in spatiotemporal baseline interfaces and graph-mainly based detection have demonstrated the effectiveness of integrating spatiotemporal feature representations for predictive analytics packages [17,18].

4. Results and Discussion

R2 Score: The sum of squares is the sum of the residuals squared and the sum of squares is the sum of the squared difference between the data and the mean.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2} (3)$$

MSE: The MSE is a measure of the errors of statistical models. It computes the mean of the squares of the differences between the observed and the expected values. The MSE is zero when there are no mistakes in the model. As the model grows larger, the number of the model error increase. The number is also called the MSD.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad (4)$$

RMSE: The RMSE indicates the difference between the results of a statistical model and the actual results. It is known as the standard deviation of the residuals in math terms. The residuals show how far away the data points are from the regression line.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} ||y(i) - \hat{y}(i)||^2}{N}} \quad (5)$$

As seen in Table (1), the performance measures of the algorithms show that Hybrid CNN+BiLSTM performs better than others, as it has the highest R2 Score (0.907844) and the lowest error values (MSE and RMSE) indicating its ability to predict traffic.

Table.1 Performance Evaluation Table

Algorithm Name	R2score	RMSE	MSE
Propose AI CNN	0.854210	0.097243	0.009456
Extension Hybrid CNN+BiLSTM	0.907844	0.089384	0.007989
Extension Hybrid CNN+BiGRU	0.885181	0.092786	0.008609

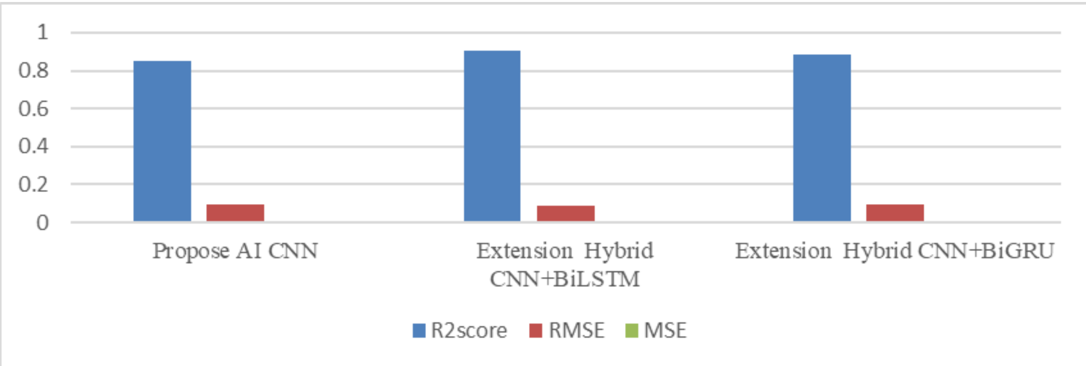

Fig.2 Performance Comparison of Models

This fig (2) shows the R2 score in blue, the RMSE in orange, and the MSE in green. The Hybrid CNN+BiLSTM model outperforms the other models on all the metrics. These results are clearly illustrated in the above graphs.

Run all of the flask blocks in the screen above to start the flask server. Next, go into a browser, enter 127.0.0.1:5000/index and press enter to view the page below.

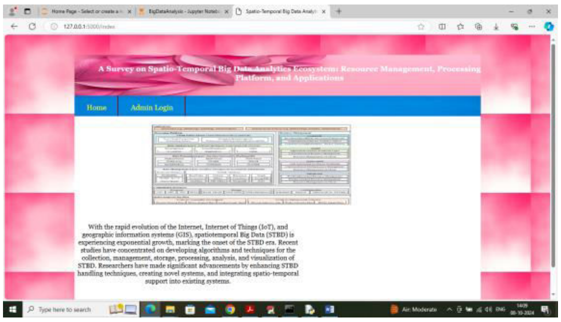

Fig.3 System Home Page

To go to the page below, click the "Admin Login" link in the above fig 3.

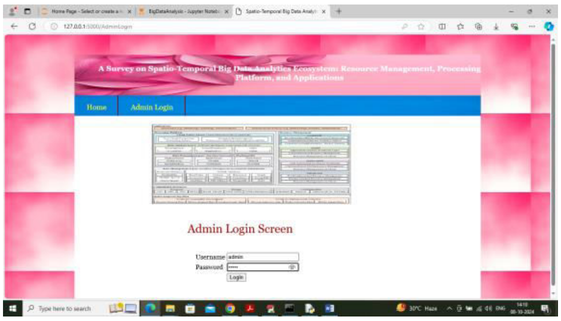

Fig.4 Administrator Login Interface

The above fig 4 shows that admin is logged in. After logging in, you'll see the following page.

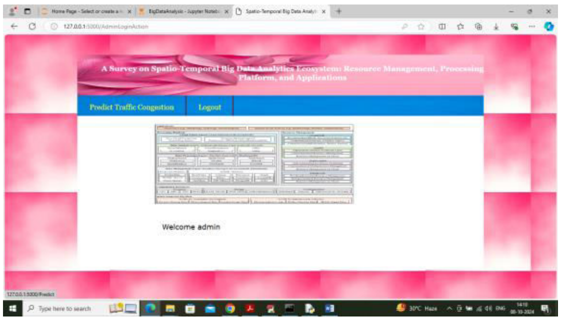

Fig.5 Main Dashboard Page

There is a link on this fig 5 titled "Traffic Prediction Congestion. To proceed to the page below, click on it.

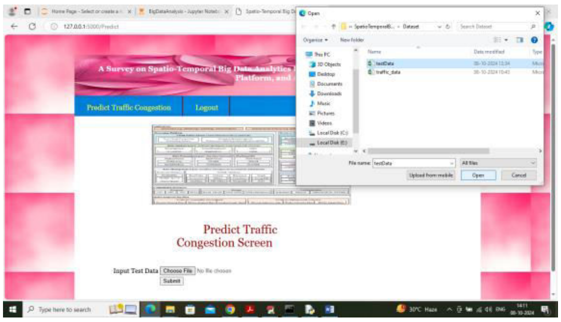

Fig.6 Traffic Congestion Prediction Interface

The fig 6 above, add the test data file from the Dataset folder. Afterward, click the "Open and submit" button and see the results.

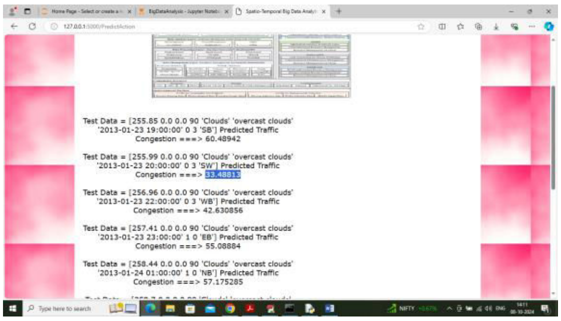

Fig.7 Traffic Congestion Prediction Results

Fig 7 shows the values from the test are displayed above in square brackets and the arrow symbol (=) indicates the percentage of traffic congestion predicted. Cops can direct traffic around the block if they believe there's going to be a lot of traffic.

5. CONCLUSION

Finally this study explores a robust approach to deal with, process and analyze STBD generated by IoT devices, particularly in traffic management. The four-layer design of the system ensures that it is easy to manage large amounts of data and ensures that it can expand as necessary. In the Data Processing Layer, Hadoop and Spark enable parallel processing to process a huge volume of complex data. Scalable storing is done using MongoDB in the Data Management Layer. CNN2D were able to properly recognize the patterns of traffic jams with a R^2 of 85%. The R^2 scores increased by 90% and 88% with the use of CNN in combination with BILSTM and BI-GRU respectively in the hybrid models. The solution is cloud-native, so it integrates seamlessly with any system and is easy to use. With over 50,000 traffic data records collected from the roads, the collection proved to be a good foundation for the model training and validation. The results suggest that the fusion of big data technology and AI models can bring useful insights for the management of traffic in real-time, monitoring healthcare and other IoT-based uses of STBD.

The goal of this system is to improve its applications in other segments of the IoT like healthcare and environmental monitoring by adding other sources of data. The mixing model can be further improved to make a more accurate prediction., too. You can even use more complicated AI models , such transformer networks or reinforcement learning . The technology could also be applied to assess information and provide decisions while it was occurring, with the potential to scale solutions in smart city buildings, autonomous vehicles, and customized medicine.

Future Scope

For future research, it could be enhanced by incorporating additional IoT data sources to enhance prediction accuracy, such as weather data, data related to events in the environment and social environment. Transformer-based models, GNNs and reinforcement learning are examples of advanced AI architectures that could be explored for improved spacial and temporal dependency modeling. By combining real-time edge and cloud computing can also lower latency and open the door for wide-spread deployment. The platform can be extended to applications of smart cities, autonomous transportation, monitoring of health and environment.

REFERENCES

[1]Alam, M. M., Torgo, L., & Bifet, A. (2022). A survey on spatio-temporal data analytics systems. ACM Computing Surveys, 54(10s), 1-38.

[2]Tian, R., Zhai, H., Zhang, W., Wang, F., & Guan, Y. (2022). A survey of spatio-temporal big data indexing methods in distributed environment. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 15, 4132-4155.

[3]Bhunia, G. S., & Shit, P. K. (2024). Big data analysis for sustainable land management on geospatial cloud framework. In Geospatial Practices in Natural Resources Management (pp. 3-17). Cham: Springer International Publishing.

[4]Gao, F., Yue, P., Cao, Z., Zhao, S., Shangguan, B., Jiang, L., ... & Liang, Z. (2022). A multi-source spatio-temporal data cube for large-scale geospatial analysis. International Journal of Geographical Information Science, 36(9), 1853-1884.

[5]Lone, M. A., & Akhtar, N. (2024, August). Spatio-Temporal Data Analytics for Intelligent Transportation Systems: An Overview. In 2024 First International Conference on Pioneering Developments in Computer Science & Digital Technologies (IC2SDT) (pp. 228-233). IEEE.

[6]Kumar, R., Bhanu, M., Mendes-Moreira, J., & Chandra, J. (2024). Spatio-Temporal Predictive Modeling Techniques for Different Domains: a Survey. ACM Computing Surveys, 57(2), 1-42.

[7]Almeida, A., Brás, S., Sargento, S., & Pinto, F. C. (2023). Time series big data: a survey on data stream frameworks, analysis and algorithms. Journal of Big Data, 10(1), 83.

[8]Yu, G., Wang, Y., Hu, M., Shi, L., Mao, Z., & Sugumaran, V. (2021). RIOMS: An intelligent system for operation and maintenance of urban roads using spatio-temporal data in smart cities. Future generation computer systems, 115, 583-609.

[9]Ale, L., Zhang, N., King, S. A., & Guardiola, J. (2021). Spatio-temporal Bayesian learning for mobile edge computing resource planning in smart cities. ACM Transactions on Internet Technology (TOIT), 21(3), 1-21.

[10]Shen, W., Zhang, J., Wang, K., & Zhang, Z. (2023). Identifying the spatio-temporal dynamics of regional ecological risk based on Google Earth Engine: A case study from Loess Plateau, China. Science of the Total Environment, 873, 162346.

[11]Chergui, N., & Kechadi, M. T. (2022). Data analytics for crop management: a big data view. Journal of Big Data, 9(1), 123.

[12]Wang, S., Zhao, X., Qiu, J., Wang, H., & Tao, C. (2024). WDCIP: spatio-temporal AI-driven disease control intelligent platform for combating COVID-19 pandemic. Geo-spatial Information Science, 27(6), 2023-2047.

[13]Firatli, E., Dervisoglu, A., Yagmur, N., Musaoglu, N., & Tanik, A. (2022). Spatio-temporal assessment of natural lakes in Turkey. Earth Science Informatics, 15(2), 951-964.

[14]Sun, M., Shi, W., Rui, H., & Huang, K. (2024, April). Research on Application of Big Data Based on Ancient Tree Monitoring. In 2024 13th International Conference of Information and Communication Technology (ICTech) (pp. 271-276). IEEE.

[15]Ding, Q., Shao, Z., Huang, X., Altan, O., & Hu, B. (2022). Time-series land cover mapping and urban expansion analysis using OpenStreetMap data and remote sensing big data: A case study of Guangdong-Hong Kong-Macao Greater Bay Area, China. International Journal of Applied Earth Observation and Geoinformation, 113, 103001.

[16] Vogklis, K. (2025). Leveraging spatiotemporal big data for sustainable destination development: an interdisciplinary approach. *Information Technology & Tourism*, *27*(4), 981-1010.

[17] Liang, Y., Wen, H., Xia, Y., Jin, M., Yang, B., Salim, F., ... & Cong, G. (2025, August). Foundation models for spatio-temporal data science: A tutorial and survey. In *Proceedings of the 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining V. 2* (pp. 6063-6073).

[18] Hairuddin, F. I., Azri, S., & Ujang, U. (2026). Graph-based Spatio-Temporal Analytics: A

Systematic Review. *Networks and Spatial Economics*, 1-50.

[19] Han, X., Li, Z., Cao, H., & Hou, B. (2025). Multimodal spatio-temporal data visualization technologies for contemporary urban landscape architecture: A review and prospect in the context of smart cities. *Land*, *14*(5), 1069.

[20] Ben Rhaiem, M. A., Selmi, M., Farah, I. R., & Bouzeghoub, A. (2026). Leveraging volunteered geographical information and spatio temporal big data in disaster management: opportunity and challenges. *International Journal of Data Science and Analytics*, *21*(1), 25.