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Enhancing Urban Crowd Monitoring through Predictive Modelling System with Diverse Geospatial Datasets

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Research-in-progress

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Abstract

The escalating urban population had resulted in social and safety challenges. Therefore, effectively managing crowd congestion in densely populated cities became of utmost importance in urban governance. In order to address urban challenges, we proposed a monitor model based on the GRU time-series model, integrating data from telecommunications, ticket sales, events, weather observations, and parking availability to predict and control urban crowds. In this study, the GRU model outperformed LSTM and GRU-Attention models due to its efficiency. Taking six types of hourly data from the past 48 hours as input, it forecasted tourist flow at attractions five hours ahead. Additionally, a visualization system was developed to allow users to analyze historical data, specific attractions, and prediction times. The proposed system offered valuable tools for urban crowd monitoring, facilitating informed decision-making, resource allocation, and efficient governance and tourism activities.

Keywords smart city governance, crowd monitoring system, predictive modelling, geospatial deep learning application

1 Introduction

According to the United Nations population estimates and projections, by 2050, up to two-thirds of the global population (approximately 5 billion people) will reside in urban areas. The overwhelming population has led to social and safety issues. Managing crowd congestion in highly dense cities is considered a crucial task in urban governance as it can impact public safety (Feliciani et al., 2023). Some cities have started collaborating with telecommunications companies to monitor the crowd instantaneously (Anthopoulos et al., 2010). However, reliable prediction methods are still lacking (Sidiropoulos et al., 2020). In the absence of accurate predictions of crowd movements, governments are unable to anticipate the timing and scale of crowd occurrences, leading to ineffective control methods.

Past literature revealed the ways in which crowd monitoring is commonly practised in today's urban governance. Techniques based on real-time images or Internet of Things (IoT) data for estimating the current situation of the crowd had been mature and had been commonly used worldwide (Reffat, R., 2012; Huang, S., 2023). In order to provide prompt warning before a crisis, anomaly detection methods and notification systems had been developed (Bamaqa et al., 2022). These previous studies had shown that crowd movements can be effectively managed and that data monitoring can indeed help to prevent the occurrence or expansion of a crisis. However, these methods were unable to predict dynamics far into the future. This gap inspired us to develop a practical prediction model of crowd dynamics.

In this study, a monitoring model for controlling and predicting urban crowds based on diverse datasets was proposed. In order to make valid predictions about the crowds, a monitoring system is developed in the present study. The system is designed to collect several kinds of crowd-related data automatically or input manually. The system model was based on the multi-factor input time-series model Gated Recurrent Unit(GRU), and was compared with Long Short-Term Memory (LSTM) Model and GRU-Attention Model. This breakthrough has the ability to significantly expand prediction time and therefore improve the efficiency of urban governance.

In the following section, the development methodologies of this system were first explained, followed by a result description of the potential application and the demo website design. Finally, the conclusion of this study is stated.

2 Research Method

In this study, the urban crowd monitoring system was developed to collect and display real-time datasets and future forecasts. The research method was divided into two main steps: I. data collection and processing, and II. prediction modelling (refer to Figure 1). Eventually, the collected data and predictive models were displayed and applied in a monitoring dashboard.

In the initial phase, six types of data which were found to exhibit a strong correlation with crowd size were collected. To convert these data into the same time series, different methods were employed for data preprocessing. The resulting time-series data were then utilized in a Multi-Step Multivariate Time Series Forecasting (Lim et al., 2021) by using LSTM, GRU, and GRU-A models.

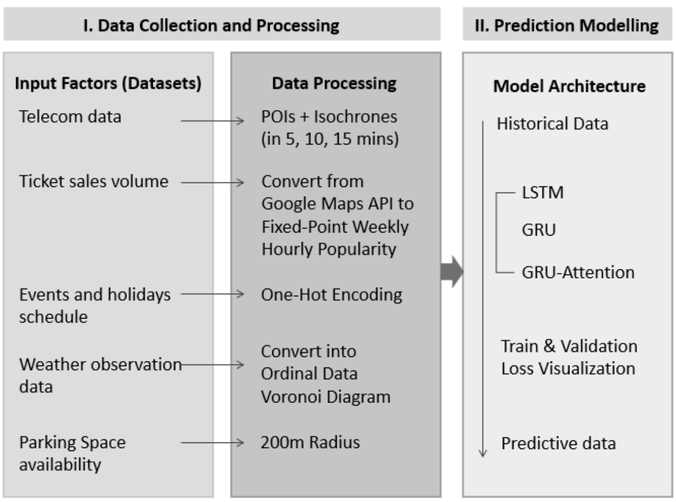

Figure 1: System Architecture

2.1 Datasets and Data Processing

The study domain of this study was defined as 5 tourist attractions in Tainan City based on the adequacy of data, including Chikan Tower, Confucius Temple, Guohua Haian Shopping Area, Anping Street and Harborfront (refer to Figure 2). These areas were popular and represented five different types of tourist attractions in Tainan's urban area, namely historical buildings, religious buildings, shopping areas, old towns, and seasides. To improve the accuracy of prediction, 6 types of data were utilized as input factors in this study, including historical crowd data converted by telecommunications data, attractions ticket sales volume, events and holidays schedule, weather observation data (including air temperature and rain amount), and parking space availability. These data were selected due to our hypothesis that they might directly reflect crowd size or be related to people's inclination to gather.

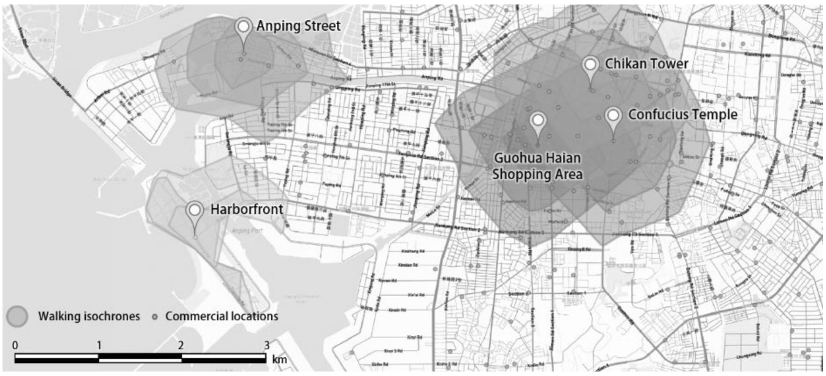

Figure 2: Attractions and their Walking Isochrones (5, 10, 15 minutes) for Commercial Locations

2.1.1 historical crowd data (telecommunication data)

Given the prevalence of private communications, telecommunication data had emerged as a valuable indicator of crowd congestion. For this research, we utilized historical crowd data obtained from Far EasTone Company and the Tourism Bureau, Tainan City Government, which was converted from telecommunication data, for five attractions. The actual number of people at the attractions is estimated based on the number of telecom service users and the population of Taiwan, since our method by using the telecom data compared to the original method with trip distribution is more precise in practical implications. In this research, the dataset spanned hourly records from July to August 2022.

In order to assess the dispersion of tourists, we employed walking isochrones for each attraction with varying impact radii (5, 10, and 15 minutes) and intersected them with Points of Interest (POI) in the vicinity (see Figure 2). The POI data, encompassing restaurant, commerce, hotel, transportation, parking, and facility categories, was collected through web crawlers and government open data sources. The correlation analysis conducted between the attractions' ticket sales volume data and the telecommunications data provided by Far EasTone Company demonstrates a strong positive correlation of +0.8. This indicates a high degree of positive correlation between the telecom data and the actual ticket sales situation, thus validating the credibility of the telecom data. In the end, the ticket sales end up being the most important factor, see Figure 3.

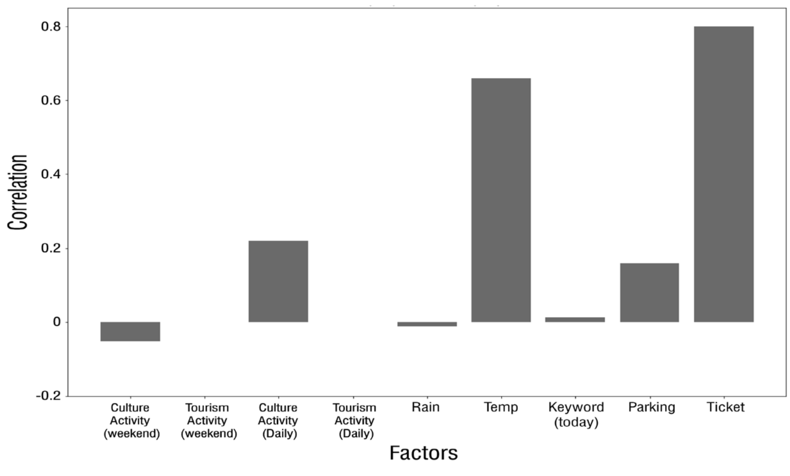

Figure 3: Comparison of Factors Importance.

2.1.2 attractions ticket sales volume

To ensure the accuracy and reliability of the historical crowd data obtained from telecom sources, it was crucial to cross-reference with other data streams displaying similar peaks and valleys. Ticket sales volume was identified as an effective proxy for crowd levels, reflecting visitor numbers at attractions. Government statistics provided us with daily ticket sales volume for each attraction. However, since the sales data was not available on an hourly basis, we needed to devise a method to obtain hourly crowd estimates.

In this study, we leveraged the Google Maps API (Svennerberg et al., 2010) to obtain the hourly popularity level (p) at fixed locations every week. By converting the total number of tickets sold on a given day (T) and matching it with the corresponding weekly popularity level, we were able to derive the hourly ticket data (h). This process is represented by Equation (1):

$$h = \begin{bmatrix} h_0 \\ \vdots \\ h_{23} \end{bmatrix}, hourly\ sold\ ticket$$
$$p = \begin{bmatrix} p_0 \\ \vdots \\ p_{23} \end{bmatrix}, hourly\ popularity\ rate$$
$$T = total\ volume\ of\ sold\ ticket\ on\ the\ day$$
$$h = \frac{T}{\sum p} \times p$$

2.1.3 events and holidays schedule

In this study, holidays and events emerged as primary factors significantly influencing crowd dynamics. Acknowledging the pivotal role of the daily schedule, special emphasis was placed on considering it as a crucial factor.

To effectively capture days with anticipated large crowds, we employed one-hot encoding to label weekends, holidays, festivals, and events. The dataset used for this purpose was sourced from the Tainan City Government's 2022 calendar, allowing us to establish correlations between each event and crowd volumes. By marking congested days with this approach, we aimed to enhance the efficiency of urban monitoring and reduce the likelihood of accidents. This proactive measure contributes to better crowd control and fosters safer urban environments.

2.1.4 weather observation data (air temperature and rain amount)

Weather conditions played a pivotal role in shaping people's inclination to participate in outdoor activities. In this study, we focused on two significant factors during the summer in Tainan: high temperature and rainfall, which can influence people's willingness to venture outdoors.

To gather weather data for Taiwan, we utilized the Central Weather Bureau Observation Data Inquire Service (CODiS) publicly available resource (Central Weather Bureau of Taiwan, 2022). The dataset provided valuable information, including temperature and rainfall data. To pinpoint the representative range of weather stations, we employed the Voronoi diagram algorithm (She et al., 2015) to effectively divide the map, guiding us in determining the observation stations relevant to each attraction's location.

Considering the possibility of a non-linear relationship between rainfall intensity and people's reluctance to engage in outdoor activities (Lee et al., 2020), we categorized rainfall intensity into four classes (0, 1, 2, 3) based on the actual amounts of rainfall. This approach ensured a comprehensive and nuanced analysis of how varying levels of rainfall impact people's passivity towards outdoor pursuits.

2.1.5 parking space availability

Since private transport is the primary mode of travel for tourists in Taiwan, it's important to consider its impact on tourist congestion. Therefore, incorporating parking data into the model and using it to assess mobility and the influx and outflux of visitors to the area could be a valuable factor in evaluating tourist crowd patterns at attractions. Vehicle-related historical statistics can offer valuable insights into the transportation patterns of people gathering at specific locations. For this study, parking space availability data were sourced from the Department of Transportation, Tainan City Government. Employing GIS technology, we extracted parking spaces located within a 200-meter radius of each attraction. Hourly records of parking space availability were meticulously recorded. By conducting a comparative analysis between the peak hours of crowd gatherings and the corresponding hourly parking space availability, we gained a deeper understanding of the transportation habits exhibited by the crowds. This analysis shed light on how visitors choose to commute to these attractions, providing valuable information for urban transportation planning and crowd monitoring strategies.

2.2 Model Architecture

To forecast the possible growth of the crowd, the datasets mentioned above were utilized to build predictive models. We conducted a comparative analysis of three predictive models: LSTM (Yu et al., 2019), GRU (Fu et al., 2016), and GRU-Attention (GRU-A) (Du et al., 2018), to forecast future surges in tourist crowds across multiple individual attractions. After experimental evaluations, we found that all three models yielded similar Mean Absolute Percentage Error (MAPE) values, approximately 30%. Consequently, we opted for the GRU model due to its relatively fewer model parameters (6,502,677), making it computationally efficient, see Table 1 and Figure 4.

The chosen GRU model receives six types of hourly data from the previous 48 hours as input and predicts the tourist flow at various attractions 5 hours ahead, see Figure 5. It is noteworthy that the reduction in MAPE by 63.1% when predicting tourist flow 5 hours ahead, as compared to predicting it over 24 hours, is a significant improvement. By leveraging our visualization system, users can explore the influence of pertinent factors on tourist numbers, based on historical data intervals, specific attractions, and prediction times. This system empowered decision-makers and stakeholders to make informed assessments and enhance crowd monitoring strategies effectively.

Model	GRU-A	GRU	LSTM
# of Parameters	7,348,230	**6,502,677**	8,649,141
MAPE	0.33	**0.27**	0.30

Table 1. Models Comparison

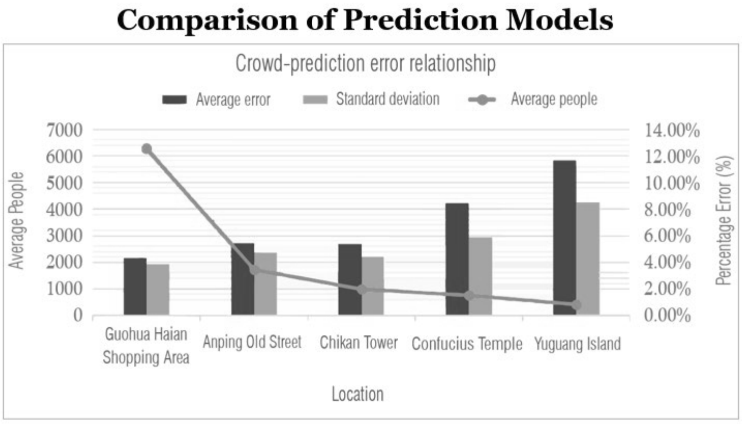

Figure 4: Comparison of Prediction Models

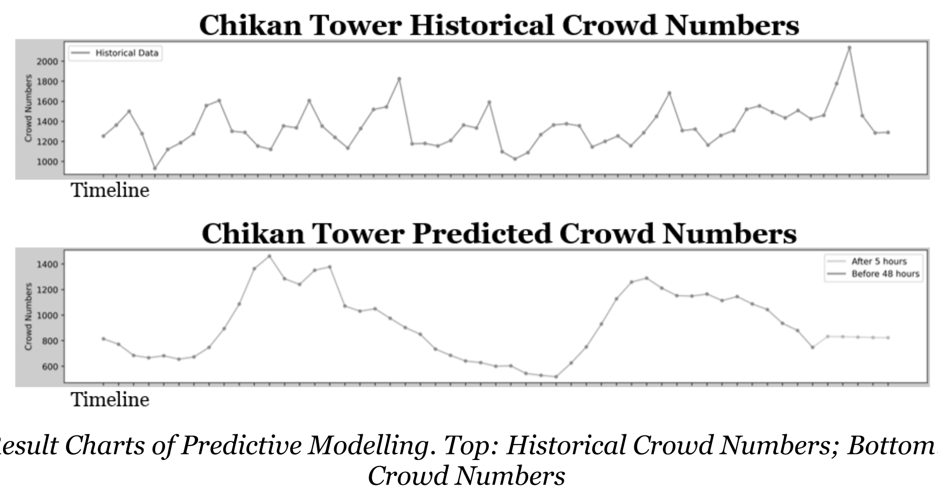

Figure 5: Result Charts of Predictive Modelling. Top: Historical Crowd Numbers; Bottom: Predicted Crowd Numbers

3 Result and Application

Building upon the defined factors influencing tourist flow and the predictive model architecture in the previous section, this study designed a crowd activity monitoring system. This system provided a filtering interface to select time and relevant factors, allowing municipal authorities to systematically review and analyze strategic directions, feasibility, and implementation benefits when formulating tourism activity monitoring strategies. It aimed to identify public infrastructure with high potential demand, thus enhancing the value of tourism. For example, by employing the analytical approach presented in this paper to analyze climate and tourist volume data at various attractions in the city, suitable locations for installing shaded and comfortable facilities were able to be determined. It could also identify the need for additional public transportation stops or the areas where routes need to be extended.

3.1 Application of Prediction Model

The crowd volume prediction model revealed the potential timeframe for data acquisition and its relationship with model training, as depicted in Figure 6. Some data was able to be acquired before the present moment, including event dates and times, historical keyword search volume, pre-sale ticket quantities for events like concerts, and weather forecast data provided by the Central Weather Bureau (available one day prior). Real-time updated data sources within government agencies, such as real-time tourist flow data, current weather observations, keyword search volume for the day, and roadside parking space usage data, were readily accessible. Additionally, agencies compiled relevant statistical data daily or monthly, like total daily ticket sales for tourist attractions or monthly revenue reports. Integrating these diverse datasets into a seamless flow model, along with manual input parameters, ensured efficient and accurate model training. In the future, establishing a comprehensive data flow system by the municipal government is expected to enable real-time monitoring and precise forecasting with continuous optimization.

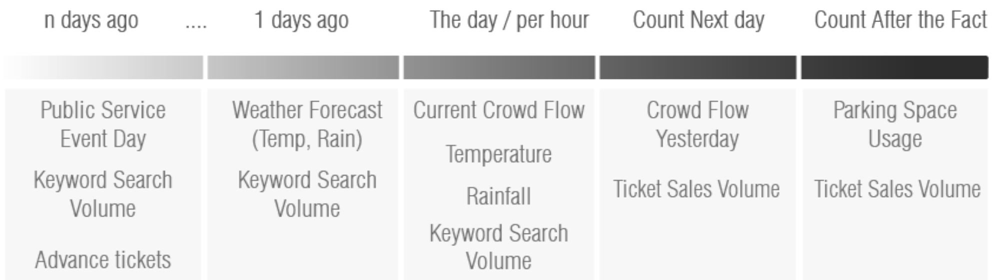

Figure 6: The Relationship between Training Factors and Time in the Predictive Model of this Study

The predictive model could leverage existing and historical tourist flow data before the present moment for learning, providing a preliminary prediction. Continuously inputting real-time data refined the model's accuracy during training. Post-event statistical data was able to validate the model's effectiveness. Users could select relevant factors and time intervals to generate real-time predictions of future tourist flow conditions.

3.2 Demo System

We crafted a user-centric interface for this initiative. In order to introduce this research into urban governance, the system was segmented into three core pages: the Map, Statistics, and Event Scheduling. The Map page offered insights into historical, present, and predictive crowd distributions, along with other geographic data. The Statistics page showcased the movement of individuals at specific sites during designated times. Meanwhile, the Event Scheduling page allowed users to view and edit historical and future event schedules.

The system's web UI was penned in the R language, leveraging the Shiny App framework (Haddaway et al., 2022) for R. Additionally, Python bolstered our analytical prowess, handling training and prediction tasks. The interface was adaptive, allowing users to modify time frames and influencing factors. Our application utilized shape file data from OpenStreetMap (Vargas-Munoz et al., 2020) to provide rich geographical information. This enabled administrators to visualize and explore scenic areas on interactive maps, making it easier to understand the spatial distribution of data and identify trends or patterns, see Figure 7.

Figure 7: Screenshot of demo system webpage. Left: Interactive Map; Right: Data Monitoring Dashboards

To enhance the functionality and visualization capabilities, the application incorporated various R packages such as tidyverse, lubridate, zoo, data.table, leaflet, and scales. These packages offered a wide range of tools and functions for data manipulation, visualization, and interactive dashboard creation for viewing the status of tourist flow. As shown in Figure 7, the dropdown menu on the left side of the interface allowed users to select the type of data to view and the visualization format, such as geographical and pedestrian distribution at attractions, data monitoring dashboards, and more. Administrators were able to select the desired data targets, such as historical data intervals, attractions, and prediction time (1-5 hours), among others. Whether the users used the system website for analyzing historical data, predicting future trends, or exploring geographical patterns, our application provided a robust and user-friendly platform for efficient data exploration and visualization.

4 Conclusion

In this study, we developed a comprehensive monitoring system for crowd monitoring and prediction in urban areas, specifically targeting administrative agencies as the primary user group.

To ensure the system's effectiveness, we incorporated various input factors, including data from telecommunications, ticket sales, events and holidays schedules, weather observations, and parking space availability. These factors were meticulously processed using advanced methods to convert them into time-series data, optimizing the system's predictive capabilities.

We had a comparison of three prediction models: LSTM, GRU, and GRU-A. After rigorous evaluation, we adopted the GRU model due to its superior performance and the fewest model parameters. This decision allowed us to forecast future surges in tourist crowds at individual attractions accurately.

By employing real-time and historical data for model training and refinement and validating its effectiveness with post-event statistical data, our system achieved reliable predictions. Users were able to customize the system to generate real-time forecasts of future tourist flow conditions, empowering them to make data-driven decisions and enhance crowd monitoring strategies.

Finally, a user-friendly demo system was developed, featuring an intuitive web-based interface designed with R language for the UI and Python for training and prediction. The system's functionality included interactive maps, data monitoring dashboards, and customizable visualization formats, ensuring ease of use and accessibility for administrators. The application of the system was particularly geared towards crowd activity monitor and strategic decision-making in tourism activity monitor. By analyzing factors that influence tourist flow and harnessing the predictive model's capabilities, municipal authorities were able to identify infrastructure needs, determine suitable locations for facilities, and optimize transportation routes or extensions.

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