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Smart Public Art: Leveraging IoT and Digital Technology in Ganzhou's Public Spaces

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Abstract

Public areas can have Internet of Things (IoT)-enabled sensing devices placed to keep track of possible security risks such as suspicious activity or misplaced possessions. In public areas, devices have the ability to gather information, but, in some cases, people must explicitly check out if they wish their data to be taken. This research presents an analysis of the IoT environment on Ganzhou's public transportation, suggests a new IoT-based intelligent public transportation system framework, and shows how the communication network's components are being applied. In this study, we detail the deployment of IoT sensors through the collection of data. We proposed a novel Salp Swarm weighted recurrent neural network (SS- WRNN) for prediction in Ganzhou's public transport flow. The data were extracted using linear discriminate analysis (LDA) from high-dimensional sensor data into a lower-dimensional space. For resolving the dynamic bus scheduling and controlling issues, decision support algorithms are suggested. It can help decision-makers decrease passenger trip times, boost scheduling effectiveness, and raise the rate at which transportation resources are utilized.

Keywords: Public Space, Smart Art, Internet of Things (IoT), Ganzhou, Salp Swarm Weighted Recurrent Neural Network (SS-WRNN).

1. Introduction

IoT and virtual generation are revolutionizing city spaces internationally through enhancing connectivity, efficiency, and comfort. In the context of an ancient metropolis, these advancements are remodeling public areas into smarter, greater lives for residents and traffic, selling sustainable development, and fostering economic growth.

1.1 Smart infrastructure

IoT includes upgrading its public infrastructure to encompass smart avenue lighting, waste control systems, and transportation networks[1]. Smart streetlights, equipped with sensors and associated with management systems, can modify brightness based on real-time data, thereby lowering energy. Similarly, IoT-enabled waste containers can notify series offerings while they're full, making sure of timely waste disposal and cleaning public areas[2].

1.2 Improving public safety and services

Digital generation performs an important function in improving public safety. A surveillance digital camera with facial reputation talents, emergency reaction systems, and predictive policing tools is being deployed across the metropolis[3]. These technologies help regulation enforcement businesses show and respond to incidents more correctly, growing a stable environment for residents and tourists alike. IoT and the virtual era are streamlining public offerings.

1.3 Promoting environmental sustainability

Leveraging IoT to advance environmental sustainability. Smart water control structures monitor water quality and intake, while air quality sensors provide actual-time statistics to help mitigate pollution[4]. These initiatives not most effective shield the environment but additionally contribute to the health and well-being of the metropolis's populace by ensuring purified air and water.

1.4 Community engagement and virtual inclusion

Digital technology is fostering extra network engagement. Interactive kiosks, mobile apps, and social media systems enable residents to get admission to statistics, participate in the nearby decision-making procedure, and provide feedback on public offerings[5]. Efforts to advance digital inclusion make certain that each resident, irrespective of age or socioeconomic popularity, can take advantage of those technological improvements, bridging the virtual divide and fostering an inclusive society [6].

1.5 Aim

The purpose of this paper is to propose a Salp Swarm weighted recurrent neural network (SS-WRNN) for prediction in Ganzhou's public transport flow.

1.6 Organization

The remaining parts of this paper are Part 2 provides the related work, Part 3 presents the methodology, Part 4 represents the result and discussion and Part 5 discusses the conclusion of the paper.

2. Related work

Authors of [7] addressed several noteworthy technologies and issues that citizens encounter due to a lack of digitalization. It offered the best solutions for issues like safety, protection, and infrastructure for the public. In addition to AI, it covers the Internet of Things, neural networks, machine learning, pattern rearrangement, and big data analytics to build a fully functional smart city. The analysis highlights the primary obstacles to broad adoption and suggests a research avenue to effectively and economically solve each one, including IoT in public safety and defense.

The term smart towns was addressed in [8], along with the methods by which machine learning and IoT can be used to create a data-driven smart ecosystem. Innovations in technology were used by smart towns to improve living conditions for their citizens and boost the efficiency of public services. The results show that these developments have the ability to alter urban environments and enable the construction of more prosperous, sustainable and beneficial cities.

The operational patterns of traffic systems in smart cities, with a particular emphasis on the traffic communications network's safety and efficiency in operation were utilized to be examined in [9]. Furthermore, the standard running time was primarily lower than in prior configurations when analyzing the bus trip time variation with the model implemented, showing a gain in operational efficiency.

The issues of traffic management were addressed and the cloud-assisted IoT intelligent transportation system (CIoT-ITS) was proposed in [10]. For tracking vehicle flow, an IoT sensor-incorporated camera has been mounted at each corner of the signalized intersection. Based on the optimization parameter, the suggested system has been evaluated and shown to perform better than traditional approaches.

The possibilities of IoT and block chainin intelligent transportation and logistics, a project that seeks to advance the fields of logistics as well as transportation were examined in [11]. They provided a tiered system that incorporates IoT for smart logistics and transportation and demonstrated the use of that. According to the findings, it presented two case studies that were grounded in real-world IoT and block chain technology.

Real-time person identification techniques were focus in[12]. A visual image depicting the number of individuals who used an obstacle to access or exit public transit can be captured by a security camera, and it can be used for determining the gender of those people to determine which seats may be reserved on a bus depending on a person's. The structure was effective at analyzing data in real-time and transmitting information about the number of people moving at a given time to remote places.

3. Methodology

In this section, we provide a comprehensive explanation of the design and architecture of transport, management and dynamic bus scheduling, data, feature extraction (LDA) and proposed method (SS-WRNN).

3.1 Design

In broad terms, public transportation includes air, train, road, and marine transportation. In this article, the design of the road public transportation system takes into consideration, the most popular mode of transportation for inhabitants in an urban town which is the bus. Fig 1 shows the connectivity network of the suggested automated public transportation system.

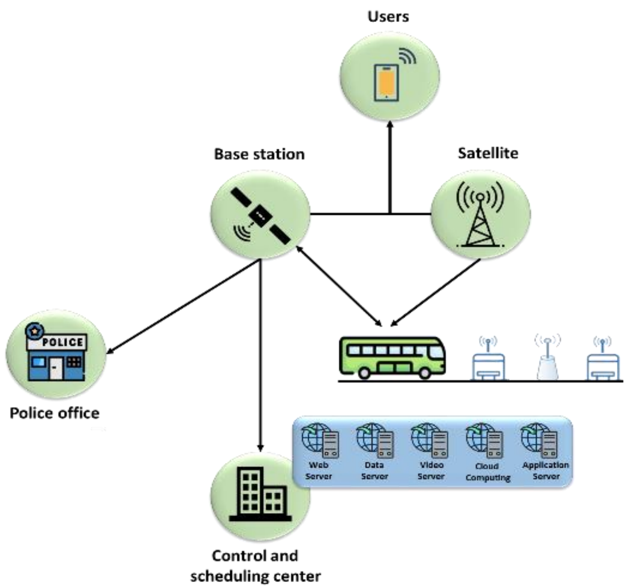

Fig 1: Connectivity network of automated public transportation system

Level 1: Users interact with the network through wireless devices, such as mobile devices, which are equipped with integrated Geographic Information System (GIS) technology and Global Positioning System (GPS) modules that transmit physical geographical data.

Level 2: Buses are equipped with a strong onboard bus unit (O-BBU), which can recognize intelligent terminals on roadways (such as lampposts) or bus stops by employing short-range wireless communication procedures. It can also send and receive data through a communications wireless network from the control and programming centers. Devices that gather real-time information on traffic conditions and passenger flow near bus stops are part of the smart interfaces. When a bus approaches, a smart terminal recognizes its radio frequency identification (RFID) tags, connects with the bus's O-BBU, obtains information from the O-BBU, and transmits the relevant data to the controller and reservation center.

Level 3: The management and bus scheduling stations gather data gathered from users and prospective consumers for additional analysis of origin-destination travel flow, develop integrated responses and transmit commands to the vehicles. It also collects data from the bus. The website server offers customers a travel search service, and the information server offers a variety of software programs for the system, which keeps track of system activity, and the recording server which conserves past surveillance footage.

Level 4: The police department monitors the operation of public transportation and responds to any requests or police calls received from the management and planning center.

3.2 Architecture

The architecture of smart public transport has three layers such as application, perceiving, and network. Fig 2 represents the architecture of IoT based system.

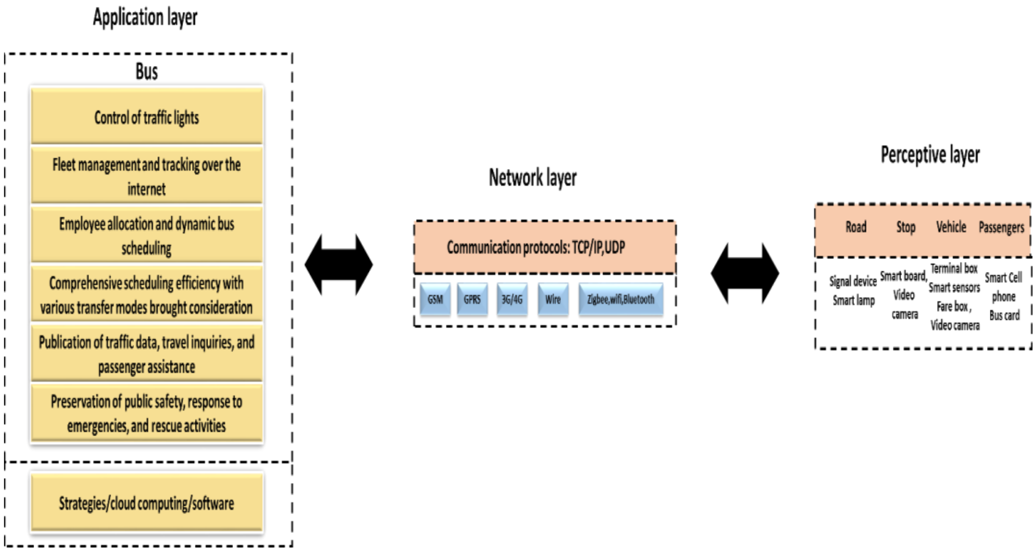

Fig 2: Architecture of IoT-based system

3.2.1 Application layer

It provides apps for users or employees of the public transportation system that analyze the data obtained from the perception component. It is separated into two sub-layers: the organization layer and the platform layer. With the help of the IoT, common techniques and algorithms are packaged as software on the platform sublayer. Green wave management and traffic light regulation can be used in the bus network to maintain the public transportation priority plan. Lastly, this component also includes emergency preparedness, rescue efforts, and a guarantee of public safety all essential components of the public's transport system.

3.2.2 Perceiving layer

IoT's source of knowledge consists of the system's many sensors and data collection tools. To be more precise, it can be separated into:

- Technology at the bus stop (eg. An intelligent touch screen to communicate with passengers in line, Automatic Vehicle Identification)
- Technology from passengers (eg. Mobile, bus card)
- Technology in public transport (eg. sensors for monitoring the outside degree and transpirationin the bus, a fare box for gathering payment data, a digital video recorder)

- Technology in road establishments (eg. signal device and smart lap poles)

3.2.3 Network layer

It is in charge of sending data from the program's application layer to the perception layer. Both wired and wireless connections are included. Public and private wireless connections are two further categories into which wireless communications can be separated.

3.3 Management system and dynamic bus scheduling

The core component of the suggested IoT-based transport system architecture is the deployment of dynamic bus scheduling and management. According to the IoT the system of public transportation is capable of utilizing information gathered from many different kinds of valuable information that can be obtained. This will increase the efficiency of the system. The dynamic bus scheduling and management system consists of four key components:

- Passenger flow analysis
- Bus planning efficiency
- Dynamic allocation optimization
- Control of vehicle improvement

The following provides a detailed introduction to the modules.

3.3.1 Passenger Flow Analysis

The mass quantity from numerous sources, in a variety of shapes, including video and actual time with variations, are the features of IoT data. Road network flow and passenger flow are examples of transportation flow.

3.3.2 Bus Planning Efficiency

The planning and managing system changes the bus plan and determines the best time for a bus to be dispatched based on real-time data gathered by IoT. The planning and management system of the public transportation system can employ specific scheduling methods, such as short turnaround and pruning, to allocate vehicles that do not stop at every bus station when it identifies abnormal road network circulation or passenger flow.

3.3.3 Dynamic allocation optimizing

The arranging and overseeing system determines the best time to send vehicles by continually altering scheduling plans based on current data gathered by IoT. The bus scheduling and management system can employ specific scheduling methods, such as short turnaround and pruning, to assign cars that are not stopped at each bus station when the general transportation method's IoT identifies unusual user or roadway traffic.

3.3.4 Control of vehicles improvement

The arrangement and regulating system change a new screw membership to the automobile if an emergency scenario involving the vehicle screw occurs, such as a driver being ill, being incapable of driving, or being temporarily redeployed, to minimize the effects of an assignment modification.

The aforementioned components of the dynamic bus scheduling and management system are created by using operational research concepts and formulating optimization problems under various scenarios.

3.4 Data

The public transportation provider that runs the bus route supplied the real-time passenger flow data as well as the real-time bus running speed data for five days. The bus route is 15 kilometers long with 20 stops. Two nearby stops are typically separated by 0.5 kilometers. The line's buses can accommodate up to 45 passengers. When taking into account the waiting time for traffic lights, the bus's average speed of travel ranges from 6 to 14 km. For a single passenger, the median time to board and get off is roughly 8 seconds, and we used the first six months to calculate the trip timing.

3.5Feature extraction

We use linear discriminate analysis (LDA) for feature extraction. LDA can help perceive styles and distinguish between distinctive classes of delivery usage primarily based on historical facts. This permits greater accurate forecasting of passenger numbers and top utilization times. Implementing LDA aids in optimizing resource allocation and enhancing the efficiency of general public transportationdevices.

Let us consider an initial collection of N instances $\{W^1 \ldots W^M\}$, where W^j is an array vector of dimension d for each sample. Every training instance is associated with a certain L class. Let $m_l = |D_l|$ represent the total quantity of instances in class $l = 1 \ldots L$, and let D_l be the total number of every instance in the class. The within-class and between-class scattering matrices in LDA are calculated as follows:

$$T_\omega = \frac{\sum_l \sum_{j \epsilon D_l} (W^j - n_l)(W^j - n_l)^S}{M}, T_a = \frac{\sum_l (n_l - n)(n_l - n)^S}{M} \quad (1)$$

Where $n_l = \frac{1}{n_l} \sum_{j \in D_l} W^j$, the L-th group mean is denoted by W^j and $n = \frac{1}{M} \sum_j W^j$. The collection's mean is represented by j. Where W is a $c \times c'$ matrices and c' is the desired amount of measurements, we search for the linear change $W \rightarrow X^S W$ that minimizes the between-class variability compared to the within-class variation. It can be demonstrated that the extended coefficients that correlate to the d′ highest eigenvalues, $T_a x = \lambda T_\omega x$, are the rows of the optimum W. The scattering vectors $X^S T_a X$ and $X^S T_\omega X$are simultaneously diagonalized by W as an outcome of this finding. LDA matches the data between and within classes.

By using the training data to fit an exponential Aggregate Modeling, the LDA predictions may be obtained. Instances of the categories described in the training data can be classified using the resulting mixed model, but not instances of the new classes. For that reason, a distinct probability model is needed, which probabilistic LDA offers.

3.6 Proposed method

We proposed the Salp Swarm weighted recurrent neural network (SS- WRNN) for prediction in Ganzhou's public transport flow.

3.6.1 Scalp swarm optimization (SS)

The SS is a bio-stimulated optimization method modeled after the swarming behavior of salps inside the ocean. For predicting public transport in Ganzhou, SS can optimize scheduling and routing by reading passenger records and visitor styles. This technique enhances performance and decreases waiting instances, making for an extra dependable and responsive public transportation machine.

The population is initially split into two categories by SS: following and leaders. The salps at the leading edge of the chain are referred to the leaders and everyone else as the followers. The salps' location is found in n-dimensions, where n stands for the number of dimensions in the issue and n denotes the exploration space of the issue at hand. These salps look for a food location, which suggests the swarm's intended destination. Since the position needs to be changed regularly, the salp leader is notified using the following equation:

$$w_i^1 = \begin{cases} E_i + d_1\big((va_i - ka_i) \times d_2 + ka_i\big)d_3 \leq 0 \\ E_i - d_1\big((va_i - ka_i) \times d_2 + ka_i\big)d_3 > 0 \end{cases} \quad (2)$$

If the meal supply in the current dimension is E_i, the leader's location is denoted by w_i^1, and the lower and upper limits correspond to va_i and ka_i. To keep the search space intact, d_2 and d_3 are created randomly in the interval [0, 1]. Furthermore, because it helps to balance the discovering and exploiting stages of the method, parameter d_1 is a crucial coefficient that is computed as follows:

$$d_1 = 2f^{-\left(\frac{4s}{s_{max}}\right)^2} \quad (3)$$

Where s_{max}stands for the maximum number of repetitions and the present iteration, correspondingly. The SSA uses the subsequent calculation to update the positions of the following after changing the positions of the leader:

$$w_i^j = \frac{1}{2}\left(w_i^j + w_i^{j-1}\right) \quad (4)$$

The i-th following location in the j-th level is denoted by w_i^j, where i is higher than 1.

3.6.2 Weighted Recurrent Neural Network (WRNN)

A WRNN can efficaciously expect Ganzhou's public transport flow with the aid of leveraging time-series statistics to become aware of patterns and tendencies. This method assigns various ranges of importance to one-of-a-kind record factors, improving the model's accuracy. By integrating actual-time and historic facts, the WRNN can offer dependable forecasts for passenger volumes, assisting optimize scheduling and resource allocation.WRNNs are an advanced form of feed-forward network.

WRNNs are strong because of their internal state, or memory cells, which are preserved and repurposed in subsequent phases as the sequences are examined one at a time. The optimal features $\{E_1^{opt}, F_2^{opt}, \dots F_m^{opt}\}$ are the input for WRNN. The resultant of its$\{Y_1, Y_2, \dots, Y_n\}$ is obtained through a series of operations carried out in the concealed vector t hid. WRNN can be expressed mathematically as follows:

$$hid_s = f_{hid}\left(hid_{s-1}, E_s^{opt}\right) \quad (5)$$

$$Y_t = f_Y(hid_t) \quad (6)$$

The result of the visible layer and the layer that is hidden is represented by the triggering variables Y_t and hid t, correspondingly. The function, which is suggested to be used inthe place of entropy function, is used to calculate the loss equation L of a WRNN.

$$L = \frac{1}{N}\sum_{j=1}^{N}\sum_m \frac{\left(Y_{(n)}^i - O_{(n)}^i\right)^2}{N} * U_n \quad (7)$$

In this case, $O_{(n)}^i$ is the expected result, $Y_{(n)}^i$ is the actual result, and N is the number of samples. Additionally, the number of subclasses is n.

3.6.3 SS-WRNN

The hybrid approach of Scalp Swarm Optimization (SS) with weighted Recurrent Neural Network (WRNN) is being utilized to expect public transport in Ganzhou. This method combines the optimization capabilities of SSO with the predictive electricity of WRNN to enhance accuracy. The WRNN improves the model's capacity to study temporal patterns in transport statistics. This hybrid version targets providingmore reliable and efficient public transportation predictions for the city. Additionally, it may help in better resource allocation and scheduling of public transport services. The final purpose is to enhance overall passenger enjoyment and operational efficiency.

4. Result and discussion

In this section, we evaluate the performance of the proposed method SS- WRNN and compare it with the existing methods(dense inception network with attention mechanism (DIN-AM)and residual neural network (Resnet) [13])based on the metrics mean absolute error (MAE), root mean square error (RMSE), and mean relative error (MRE). Then, we used the first six months to calculate the trip timing with and without optimization.

4.1 MAE

It is a measure of prediction accuracy in a regression model, representing the average absolute differences between anticipated and real values. It is calculated as the sum of the actual error value divided by the range of predictions.

$$MAE = \frac{1}{m}\sum_{s=1}^{m}\left|REI_j^{observed} - REI_j^{Predicted}\right| \quad (8)$$

MAE is particularly useful in assessing the overall performance of models predicting the flow of transport. Table 1 and Fig 3 display the evaluation of MAE. In Fig 3, the existing method DIN-AM and Resnet attained (0.0334 and 0.0286). When compared to the existing method, our proposed method SS- WRNN attained (0.0124).

Table 1: Values of MAE

Methods	MAE
Resnet	0.0334
DIN-AM	0.0286
SS-WRNN [Proposed]	0.0124

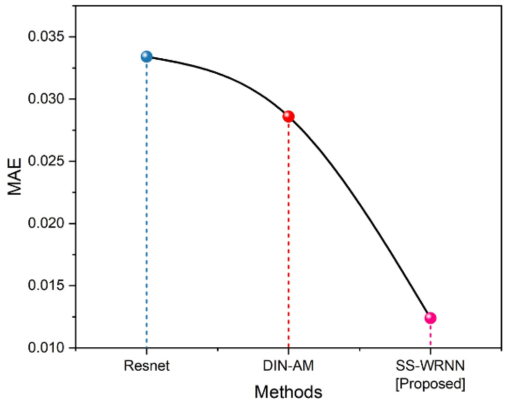

Fig 3: Evaluation of MAE

4.2 RMSE

It refers to a measure of the variations among predicted and found values for transport flow. It is calculated as the square root of the average squared difference between the predicted and actual values. RMSE provides a single level of predictive accuracy, with decreased values indicating higher model overall performance.

$$\mathrm{RMSE} = \sqrt{\frac{1}{m}\sum_{s=1}^{m}\left(\mathrm{REI}_j^{\mathrm{observed}} - \mathrm{REI}_j^{\mathrm{Predicted}}\right)^2} \quad (9)$$

Table 2 and Fig 4 represent the performance of RMSE. In Fig 4, the existing method DIN-AM and Resnet achieved (0.0449 and 0.0368) and our proposed method SS- WRNN achieved (0.0274). According to the findings, our proposed method outperformed others.

Table 2: Values of RMSE

Methods	RMSE
Resnet	0.0449
DIN-AM	0.0368
SS-WRNN [Proposed]	0.0274

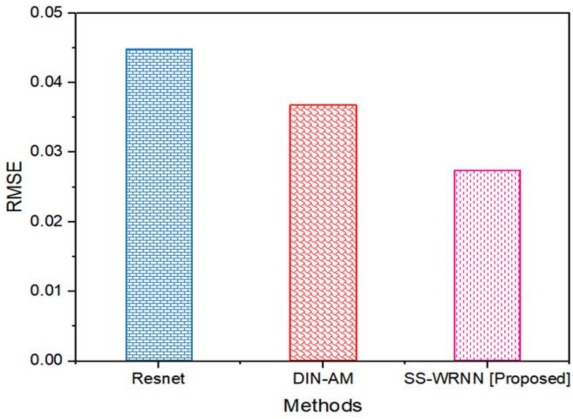

Fig 4: Performance of RMSE

4.3 MRE

It is a metric that evaluates the accuracy of a predictive method for transporting the flow. It is calculated by averaging the variations between the expected and actual values, dividing by the real values, and expressing the result as a percentage. This enables expert to determine the relative length of the errors in the actual flow values.

$$\mathrm{MRE} = \frac{1}{\mathrm{m}}\sum_{\mathrm{s}=1}^{\mathrm{m}}\left|\frac{\mathrm{Z_m}-\widehat{\mathrm{Z_m}}}{\mathrm{Z_m}}\right| \tag{10}$$

Table 3 and Fig 5 displays the evaluation of MRE. The existing method DIN-AM and Resnet attained (0.1010 and 0.0884) and the proposed method SS- WRNN attained (0.0542). When comparing our proposed method to the existing methods, our proposed method has superior performance.

Table 3: Values of MRE

Methods	MRE
Resnet	0.1010
DIN-AM	0.0884
SS-WRNN [Proposed]	0.0542

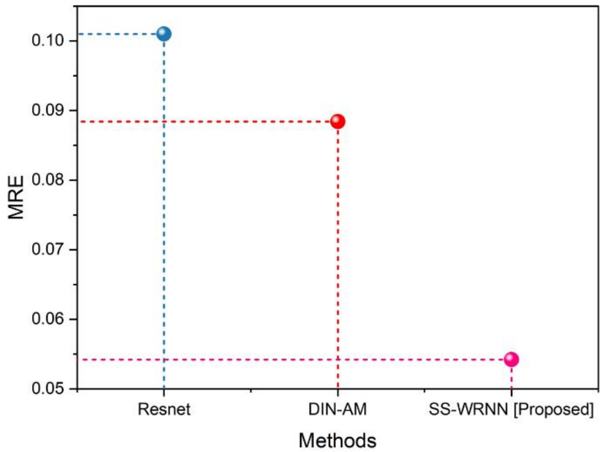

Fig 5:Evaluation of MRE

4.4 Trip timing

We evaluate the trip timing with and without optimization. Fig 6 represents the performance of trip timing. In Fig 6, with optimization, we consume (18.5, 17.8, 19, 16, 14, and 15) minutes for 1-6 months, and without optimization consume (22, 23.5, 25, 21, 20, and 19) minutes for 1-6 months. Based on the findings, optimization helps to reduce the trip timing for passengers.

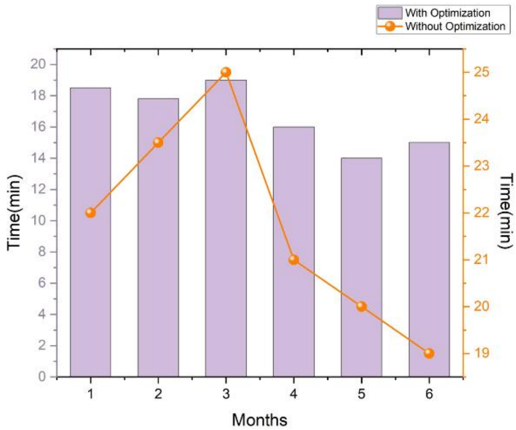

Fig 6: Performance of trip timing

5. Conclusion

IoT-enabled sensors can be installed in public spaces to monitor potential security threats like unusual behavior or misplaced property. Devices can collect data continuously in public spaces, but sometimes users have to expressly clear out to indicate that they don't want their data to be collected. This study provides a new framework for an IoT-based smart transport system and analyzes the impact of IoT on Ganzhou's public transportation. In this study, we introduced the Salp Swarm weighted recurrent neural network (SS- WRNN) for prediction in Ganzhou’s public transport flow. Data was collected by IoT sensor and we used linear discriminate analysis (LDA) for feature extraction. As a result, we evaluate the performance of our proposed method with the existing method based on the metrics MAE (0.0124), RMSE (0.0274), and MRE (0.0542). We measured the trip timing of 1-6 months based on with and without optimization. Based on the findings, our proposed method helps to reduce passenger trip timing.

5.1 Future scope and limitation

Implementing IoT-enabled sensing devices in public transportation, consisting of Ganzhou, faces challenges such as privacy concerns worries, high deployment fees, technical integration complexities, and capacity limitations in predictive model accuracy for dynamic scheduling and control. Future research can also attention on integrating superior machine-gaining knowledge of strategies with IoT frameworks to constantly improve public transportation structures' overall performance and reliability.

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