iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 **Issue:** XII **Month of publication:** December 2023

DOI: https://doi.org/10.22214/ijraset.2023.57751

Citywide Cellular Traffic Prediction Based on Densely Connected Convolutional Neural Networks

Vinay S Navale[1], Aditya A Navale[2], Hitesh Parihar[3], Kalyan B[4], Satvik A[5]
[1]B.E in Information Science & Engineering, Dept of ISE, Nitte Meenakshi Institute of Technology
[2]B.E in Computer Science & Engineering, Dept of CSE, Jawaharlal Nehru National College Of Engineering
[3]B.Tech in Computer science and engineering, Presidency University
[4, 5]B.E in Information Science & Engineering, Dept of ISE, Nitte Meenakshi Institute of Technology

***Abstract:** This paper focuses on advancing citywide cellular traffic prediction for enhancing the self-management and intelligent automation of future cellular networks. The proposed approach employs deep learning to model the complex dynamics of wireless traffic. By representing traffic data as images, the method effectively captures both spatial and temporal dependencies in cell traffic using densely connected convolutional neural networks. To refine this model, a parametric matrix-based fusion scheme is introduced, enabling the learning of influence degrees associated with spatial and temporal dependencies. Experimental results demonstrate a substantial improvement in prediction performance, measured by root mean square error (RMSE), compared to existing algorithms. The accuracy of predictions is further validated using datasets from Telecom Italia.*
***Keywords:** cellular traffic prediction; big data; deep learn ing; intelligent traffic management*

I. INTRODUCTION

The integration of traffic prediction has been widely acknowledged for optimizing resource allocation, improving energy efficiency, and enabling intelligent cellular networks [1], [2]. Recent efforts have delved into exploring the dynamic characteristics of wireless traffic, including non-stationarity and seasonality [3], to achieve accurate predictions [4], [5]. Traditional approaches treat cellular traffic prediction as a time series analysis problem, relying on linear statistical models such as AutoRegressive Integrated Moving Average (ARIMA) and alpha-stable models. However, the complexity of cellular traffic, influenced by factors like user mobility, arrival patterns, and diverse user requirements, renders these linear models unsuitable for such applications [6].

To address the complex and nonlinear dependencies inherent in wireless traffic data, recent advancements in machine learning models [7] have emerged as formidable alternatives to classical statistical models for traffic prediction [8], [9]. For instance, [8] proposed a deep belief network-based prediction method to capture the long-term dependence of cellular traffic. Meanwhile, [9] aimed to exploit the spatial dependence of different cells through a strategy combining auto-encoder and Long Short-Term Memory (LSTM) network [10]. However, the learned features via auto-encoder may not fully characterize the spatial dependence of neighboring cells, and these methods predominantly focus on predicting traffic for a single cell. Furthermore, their application to citywide scale networks can be computationally expensive, requiring the simultaneous training of hundreds or even thousands of models. Motivated by these challenges, this letter introduces a novel method for citywide traffic prediction, leveraging the potent capabilities of deep convolutional neural networks (CNNs). Specifically, densely connected CNN [12], recognized as a leading deep learning architecture, is employed to collectively model the spatial and temporal dependence of traffic across different cells. The convolution operation naturally captures spatial dependence, while two CNNs address temporal dependencies (closeness and period), with their outcomes fused through a parametric-matrix-based scheme. Experimental results and comparisons affirm the effectiveness of the proposed method, demonstrating its superiority over existing traffic prediction methods.

II. OBJECTIVES

The objectives of the study on citywide cellular traffic prediction based on Densely Connected Convolutional Neural Networks (CNNs) can be outlined as follows:

1) *Modeling Nonlinear Dynamics:* The primary objective is to develop a robust predictive model for citywide cellular traffic that can capture the nonlinear dynamics inherent in wireless traffic patterns. Unlike traditional linear models, the study aims to leverage the powerful capabilities of Densely Connected CNNs to handle the complexity of traffic data.
2) *Spatial and Temporal Dependence:* The study seeks to address both spatial and temporal dependencies in cellular traffic. By treating traffic data as images, the spatial relationships between different cells are effectively captured using the convolutional operations of the CNN. Additionally, the model aims to account for temporal dependencies, including closeness and period, to enhance the accuracy of predictions.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue XII Dec 2023- Available at www.ijraset.com

3) *Parametric Matrix Fusion:* Introducing a parametric matrix-based fusion scheme, the research aims to refine the integration of spatial and temporal dependencies. This fusion scheme is designed to learn the influence degrees of spatial and temporal factors, contributing to a more comprehensive understanding of the complex interactions within citywide cellular traffic.
4) *Efficiency and Scalability:* Considering the computational challenges associated with citywide scale networks, the study emphasizes the efficiency and scalability of the proposed method. Densely Connected CNNs are chosen for their advanced architecture, which allows for collective modeling without the need for training numerous individual models, addressing the computational expense.
5) *Performance Evaluation:* The research aims to evaluate the prediction performance of the proposed method using metrics such as root mean square error (RMSE). Comparative analyses against existing algorithms and methods serve to validate the effectiveness and superiority of the Densely Connected CNN-based approach in citywide traffic prediction.
6) *Real-World Validation:* To validate the practical applicability of the proposed method, the study employs real-world datasets, including those from Telecom Italia. This real-world validation ensures that the developed model can provide accurate predictions in diverse and dynamic urban environments.

III. LIMITATIONS

Citywide cellular traffic prediction using Densely Connected Convolutional Neural Networks (DC-CNN) faces several limitations. Firstly, the model's performance heavily relies on the availability and quality of input data, and any inaccuracies or gaps in the data may lead to suboptimal predictions. Additionally, the computational complexity of DC-CNNs can be high, posing challenges for real-time prediction in large-scale urban environments. The model may struggle to adapt to dynamic and rapidly changing traffic patterns, as its training data might not fully capture the diversity of scenarios that can occur in a city. Furthermore, DC-CNNs may suffer from interpretability issues, making it challenging to understand the rationale behind specific predictions, which is crucial for gaining trust and acceptance in practical applications. Finally, the deployment of such models may require significant computational resources, limiting their feasibility in resource-constrained settings.

IV. LITERATURE SURVEY

The literature survey [1] conducted by Li et al. (2017) explores the intersection of cellular networks and artificial intelligence (AI) in the context of 5G technology. The authors delve into the concept of "Intelligent 5G" and provide a comprehensive overview of how the integration of AI techniques can enhance the capabilities and efficiency of cellular networks. The survey covers various aspects, including intelligent resource allocation, network optimization, and the application of machine learning algorithms in managing and improving 5G performance. The paper not only highlights the potential benefits of incorporating AI into cellular networks but also discusses the challenges and future research directions in this rapidly evolving field. Overall, the survey contributes valuable insights into the symbiotic relationship between 5G and artificial intelligence, shedding light on the promising opportunities and complexities associated with this convergence.

Saxena, Sahu, and Han (2014) [2] present a literature survey in their work focused on "Traffic-aware energy optimization in green LTE cellular systems." The study investigates strategies to enhance energy efficiency in Long-Term Evolution (LTE) cellular networks with a particular emphasis on minimizing energy consumption while considering traffic patterns. The authors explore various approaches, such as dynamic traffic-aware base station sleep mode strategies and adaptive resource management, to optimize energy usage in LTE systems. By synthesizing existing research, the survey provides insights into the key challenges and potential solutions for achieving green communication in cellular networks. The emphasis on traffic awareness reflects a nuanced understanding of the dynamic nature of network demands, highlighting the need for adaptive and intelligent energy-saving mechanisms. This survey contributes to the broader discourse on sustainable and energy-efficient design principles for LTE cellular systems.

D'Alconzo, Coluccia, Ricciato, and Romirer-Maierhofer (2009) [3] contribute to the literature with a distribution-based approach to anomaly detection, focusing on its application to 3G mobile traffic. The paper introduces a method for anomaly detection that relies on statistical distributions to characterize normal behavior in 3G mobile networks. By analyzing the distribution of key network parameters, the authors aim to identify deviations indicative of anomalous activities or potential security threats. The survey encompasses the proposed distribution-based anomaly detection framework and its application specifically within the context of 3G mobile traffic. This approach addresses the critical need for effective anomaly detection mechanisms in telecommunications networks, emphasizing its potential for enhancing security and robustness in 3G mobile communication systems. The paper likely discusses related works in the field and positions its approach in the broader landscape of anomaly detection techniques for mobile networks..

[4] In the realm of traffic modeling and prediction, Zhou, He, and Sun (2006) contribute a significant literature survey through their work titled "Traffic Modeling and Prediction using ARIMA/GARCH Model." The authors focus on Chapter 5 of their book, where they delve into the application of ARIMA (AutoRegressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models for traffic forecasting. The survey likely reviews existing approaches to traffic modeling, discussing the strengths and limitations of different methodologies. It is probable that the authors provide insights into the historical context of traffic prediction, emphasizing the significance of time-series analysis in understanding and forecasting traffic patterns. Additionally, the survey may explore how the ARIMA/GARCH model compares to alternative methods in terms of accuracy and applicability. By dedicating a chapter to this topic, the authors contribute to the broader understanding of traffic prediction methodologies, establishing the ARIMA/GARCH model as a viable approach within the context of traffic modeling literature.

[5] Li et al. (2017) present a literature survey focused on "The learning and prediction of application-level traffic data in cellular networks" within their work published in the IEEE Transactions on Wireless Communications. The authors likely review existing research related to the learning and prediction of application-level traffic in the context of cellular networks. The survey likely addresses key challenges and methodologies associated with understanding and forecasting application-level traffic patterns, emphasizing the importance of accurate predictions for optimizing network performance and resource allocation. The paper likely contributes to the existing body of knowledge by synthesizing insights from various studies, potentially exploring different machine learning or predictive modeling techniques applied to cellular network traffic data. By placing their work within the broader landscape of application-level traffic prediction, the authors likely provide valuable perspectives on the state-of-the-art approaches, potential limitations, and future research directions in this domain.

Gooijer and Hyndman (2006) [6] conduct a comprehensive literature survey titled "25 years of time series forecasting" in the International Journal of Forecasting. The authors likely review a broad spectrum of research spanning a quarter-century in the field of time series forecasting. This survey is likely to cover seminal works, methodological advancements, and the evolution of forecasting techniques over the years. It probably provides insights into the major trends, challenges, and breakthroughs that have shaped the landscape of time series forecasting. By summarizing the progress made during this extensive timeframe, the survey contributes to a deep understanding of the historical context, methodological foundations, and the ongoing development of time series forecasting. The authors likely synthesize diverse approaches, including traditional statistical methods and emerging machine learning techniques, shedding light on the overarching themes and considerations that have characterized this dynamic and evolving field.

Zhang, Cao, and Gao (2014) [7] contribute to the literature with a likely literature survey in their work on "A locality correlation preserving support vector machine" published in the journal Pattern Recognition. The authors probably review existing research related to support vector machines (SVMs) and their applications in pattern recognition, with a specific focus on preserving locality correlation. The survey likely explores the challenges and advancements in SVM-based classification techniques, emphasizing the importance of preserving local correlations to enhance the model's performance in pattern recognition tasks. The paper likely positions its proposed locality correlation preserving SVM within the broader landscape of SVM variants and alternative classification methods, discussing its advantages and potential applications. By conducting a literature survey, the authors likely contribute to the understanding of SVMs in pattern recognition, offering insights into the state-of-the-art techniques and paving the way for further research in this domain.

Nie, Jiang, Yu, and Song (2017) [8] likely present a literature survey within their work on "Network traffic prediction based on deep belief network in wireless mesh backbone networks," presented at the IEEE Wireless Communications and Networking Conference (WCNC). The authors probably review the existing body of literature on network traffic prediction, focusing on the specific context of wireless mesh backbone networks and the application of deep belief networks (DBNs). The survey likely explores previous research efforts in predicting network traffic patterns, discussing both traditional methods and emerging techniques, with an emphasis on the advantages and challenges of applying deep learning, particularly DBNs, in this domain. By situating their work within the broader landscape of network traffic prediction, the authors likely contribute to understanding the state-of-the-art methodologies, identifying gaps in the existing literature, and providing a foundation for the application of DBNs in wireless mesh backbone networks.

[9] Wang et al. (2017) likely conduct a literature survey in their work on "Spatiotemporal modeling and prediction in cellular networks: A big data enabled deep learning approach," presented at the IEEE Conference on Computer Communications (INFOCOM). The authors probably review existing research on spatiotemporal modeling and prediction within the context of cellular networks, with a specific focus on leveraging big data and employing deep learning techniques.

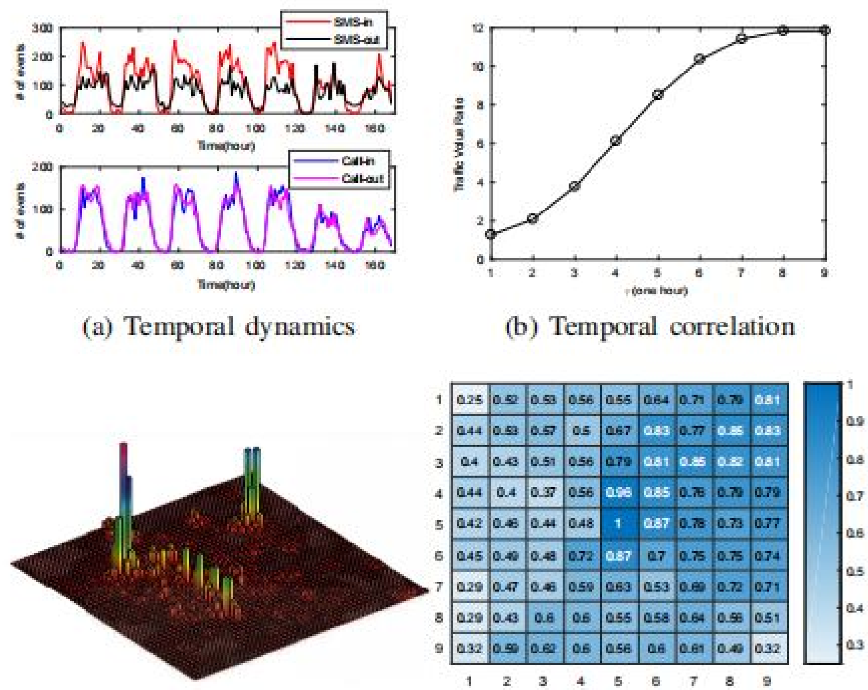
The survey likely explores traditional approaches to spatiotemporal modeling in cellular networks and compares them with emerging deep learning methodologies. By presenting their work at INFOCOM, the authors likely contribute to the conference's broader theme of advancing computer communications and networking technologies. The literature survey likely positions their big data-enabled deep learning approach within the evolving landscape of spatiotemporal modeling, identifying key trends, challenges, and opportunities for further research in the dynamic field of cellular network prediction.

LeCun, Bengio, and Hinton (2015) [10] provide a seminal literature survey on "Deep Learning" in their influential paper published in Nature. The authors offer a comprehensive overview of the field of deep learning, tracing its historical development, and highlighting key concepts, techniques, and breakthroughs. The survey likely covers a range of deep learning architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), discussing their applications in various domains such as computer vision, natural language processing, and speech recognition. The authors probably delve into the challenges and advancements in training deep neural networks, emphasizing the importance of unsupervised learning and layer-wise pretraining. By summarizing the progress made in deep learning up to 2015, the survey likely plays a crucial role in establishing the foundations of this rapidly evolving field, providing researchers and practitioners with valuable insights into the state-of-the-art techniques and guiding future developments in the realm of artificial intelligence.

V. DATASETS AND SOME KEY OBSERVATIONS

A. Wireless Big Traffic Dataset

In this letter, the wireless traffic data under analysis originates from Telecom Italia, a major telephony service provider in Europe, as part of their participation in the "Big Data Challenge" [13]. The dataset employed comprises time series data representing aggregated cell phone traffic, encompassing both short message service (SMS) and call service activities conducted by users within a specified region over the city of Milan. Milan is systematically divided into a grid format with dimensions H × W, where each grid square is termed a "cell." The dataset is configured with H=W=100, signifying that the entire city area is systematically segmented into a 100×100 grid of cells. The recorded traffic spans the timeframe from 00:00 on November 1, 2013, to 00:00 on January 1, 2014, with a temporal resolution of 10 minutes. At each time slot denoted as "t," the incoming and outgoing traffic for all cells is represented as a tensor $X_t \in R^{2\times H\times W}$, where $(X_t)_{0,i,j} = x^{in}_{i,j}$ t and $(X_t)_{1,i,j} = x^{out}_{i,j}$ t. Additionally, $x_{i,j} = \{x^{in}_{i,j}$ t $\}$, ∀t signifies the incoming/outgoing traffic of cell (i, j) without explicit differentiation, unless stated otherwise.



(a) Temporal dynamics (b) Temporal correlation

(c) Spatial distribution (d) Spatial correlation

Fig.1.Spatial and temporal distribution and correlation of the considered cellular traffic.

B. Key Observations

1) Temporal Domain

Following a meticulous examination of the dataset, we have discerned the spatial and temporal characteristics inherent in the wireless traffic, with detailed insights illustrated in Fig. 1. In the temporal domain, as depicted in Fig. 1a, the dynamics of traffic for distinct services, specifically SMS and Call services, within a given cell are revealed. Notably, the figure elucidates pronounced daily patterns, with a subtle divergence between SMS and phone call traffic. Observations from Fig. 1a highlight a consistent reduction in traffic volume during weekends in comparison to working days. Moreover, the dissimilarity in traffic volume between incoming and outgoing SMS is more pronounced than that observed in phone calls. To provide a more nuanced understanding, Fig. 1b further portrays the average traffic volume ratio at discrete time slots, represented by the time gap τ.The ratio ϱ is defined as

$$\varrho = \frac{1}{(T-\tau)\times H\times W}\sum_{t=1+\tau}^{T}\sum_{i=1}^{H}\sum_{j=1}^{W}\frac{x_t^{i,j}}{x_{t-\tau}^{i,j}},$$

Here, $x_t^{i,j}$ signifies the traffic volume recorded for cell (i, j) during the \(t\)-th time slot, and T represents the total number of time slots in the dataset. The calculated ratio is indicative of the temporal correlation within the wireless traffic time series, implying that the traffic in adjacent time slots exhibits a higher degree of relevance compared to those temporally distant.

2) Spatial Domain

In the spatial domain, focusing on SMS for illustration purposes, Fig. 1c illustrates the spatial distribution of traffic at a specific time. Evidently, the traffic is distributed disparately across various cells, a phenomenon attributed to the concentrated population in the city center, resulting in substantially higher traffic volumes compared to more rural areas. To quantify the spatial correlation in the traffic data, a widely adopted metric [9], namely the Pearson correlation coefficient ρ, is employed. This coefficient measures the correlation between a target cell (i, j) and its neighboring cells (i',j').

$$\rho = \frac{cov(\mathbf{x}^{i,j},\mathbf{x}^{i',j'})}{\sigma_{\mathbf{x}^{i,j}}\sigma_{\mathbf{x}^{i',j'}}},$$

The spatial correlation ρ is computed using the covariance operator cov(.) and the standard deviation σ . In this illustration, a region consisting of 9 × 9 cells is chosen to exemplify spatial correlations.

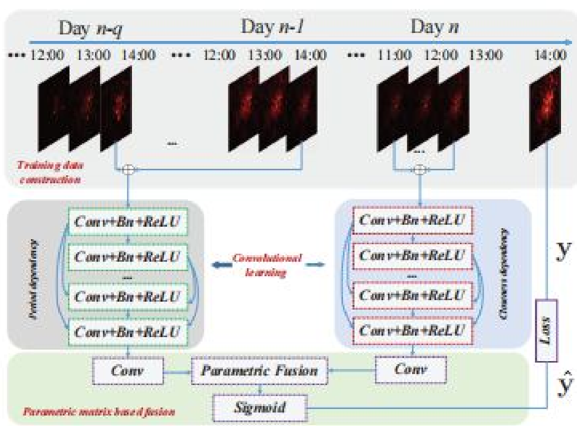


Fig.2.Prediction framework

The resulting ρ values between the target cell (5, 5) and its neighboring cells are depicted in Fig. 1d. Notably, the figure vividly indicates the presence of spatial correlation among cells, with the degree of correlation influenced by the distance between cells. For instance, while both cell (5, 4) and cell (5, 6) are equidistant from the target cell (5, 5), their correlation values, 0.48 and 0.87, respectively, differ significantly. These observations underscore the necessity for an effective methodology that can comprehensively capture both spatial and temporal dependencies within the wireless traffic dataset.

VI. PREDICTION MODEL

Within this section, we introduce a deep learning methodology grounded in convolutional neural networks (CNNs) designed to model the spatial-temporal dependencies inherent in the traffic data across diverse cells. The outlined framework is visually depicted in Fig. 2 and is primarily composed of three key components: training data construction, convolutional learning, and parametric matrix-based fusion.

A. Training Data Construction

The representation of in and out traffic for each time slot adopts a two-channel tensor matrix, resembling an image, as depicted in the upper segment of Fig. 2. To generate training and test datasets, a sliding window scheme is employed. Assuming that the traffic volume at the t-th slot serves as the target for prediction, the intervals preceding t are partitioned into two segments: recent time and daily history. Here, \(p\) denotes the length of the dependence of closeness, where the traffic from the recent time segment models the temporal closeness dependence as $[\mathbf{X}_{t-p}, \mathbf{X}_{t-(p-1)}, \cdots, \mathbf{X}_{t-1}]$ Similarly, \(q\) represents the length of the dependence of the period, with the traffic sampled from daily history modeling the temporal period dependence as $[\mathbf{X}_{t-q*24}, \mathbf{X}_{t-(q-1)*24}, \cdots, \mathbf{X}_{t-24}]$. Subsequently, the traffic in each segment is concatenated to form a new tensor along their first axis. For ease of notation, these two sampled traffic models are denoted as $\mathbf{X}_c \in \mathbb{R}^{2p \times H \times W}$ and $\mathbf{X}_d \in \mathbb{R}^{2q \times H \times W}$, respectively.

B. Densely Connected Convolutional Neural Networks

As elucidated in Section II-B2, the traffic of neighboring cells can mutually influence one another. Capitalizing on the commendable ability of Convolutional Neural Networks (CNNs) to hierarchically capture spatial structural information, we introduce CNN to model the spatial dependence among cells. By employing a kernel of size (k1, k2) in the convolution operation, the information from k1k2 cells is effectively fused into a high-level representation. Leveraging CNN, a sequence of convolutions in each layer enables the capture of both local and global spatial dependencies within the citywide traffic. Acknowledging the interdependence of in and out traffics across different cells, whether adjacent or distant, we adopt the densely connected pattern [12] in CNN. This pattern mitigates the vanishing-gradient problem, reinforces feature propagation, and ultimately enhances prediction efficiency and accuracy. The detailed network architecture is depicted in Fig. 2, featuring two networks with a shared structure—one for modeling temporal closeness dependence and the other for modeling temporal period dependence. The network comprises L layers, each implementing a non-linear transformation $f_l(\cdot), l = 1, 2, \cdots, L,$ with three consecutive operations: Convolution (Conv), Batch Normalization (BN), and rectified linear units (ReLU). ReLU, by computing the weighted sum of its input, determines whether activation is warranted. To model closeness dependence, the output at the \(l\)-th layer, denoted as , is derived from the initial input $\mathbf{X}_c^0$ at the lth layer, the output is denoted as

$$\mathbf{X}_c^l = f_l(\mathbf{X}_c^0 \oplus \mathbf{X}_c^1 \oplus \cdots \oplus \mathbf{X}_c^{l-1}),$$

In this expression, the symbol $\oplus$ denotes the concatenation of the feature maps generated in all preceding layers. Analogously, for modeling temporal period dependence, the output at the l-th layer can be expressed as:

$$\mathbf{X}_d^l = f_l(\mathbf{X}_d^0 \oplus \mathbf{X}_d^1 \oplus \cdots \oplus \mathbf{X}_d^{l-1}).$$

C. Parametric Matrix Based Fusion

Building on the preceding analysis, we understand that the traffic patterns of distinct cells exhibit relationships with both closeness and period, albeit with varying degrees of relevance. To effectively capture this relationship, we introduce a parametric matrix-based scheme designed to fuse the features of closeness and period, as depicted in the lower segment of Fig. 2. Specifically, a convolution layer is independently introduced $\mathbf{X}_c^{L+1}$ and $\mathbf{X}_d^{L+1}$ respectively.After fusion, we have

$$\mathbf{X}_o = \mathbf{W}_c \odot \mathbf{X}_c^{L+1} + \mathbf{W}_d \odot \mathbf{X}_d^{L+1},$$

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue XII Dec 2023- Available at www.ijraset.com

In these expressions, $\odot$ represents the Hadamard product, and $\mathbf{W}_c$ and $\mathbf{W}_d$ denote learnable parameters capturing the relationship between closeness, period, and wireless traffic. The ultimate output after activation is expressed as:

$$\hat{\mathbf{X}}_t = \sigma(\mathbf{X}_o),$$

In this expression, $\sigma(\cdot)$ signifies the sigmoid function. The training of the proposed deep learning model can be straightforwardly accomplished by minimizing the Frobenius norm between the predicted value and the ground truth value for the t-th time slot.

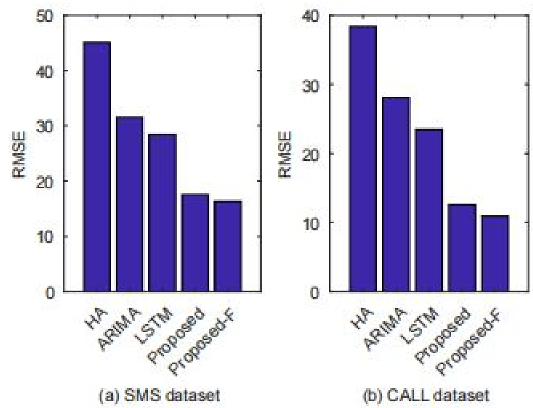


Fig.3.Overall performance on two kinds of wireless traffic.

VII. EXPERIMENTAL RESULTS AND ANALYSIS

A. Preprocessing and Parameter Settings

In this study, the authors address challenges posed by the sparsity of cell traffic data during 10-minute intervals. Due to the difficulty of resource planning at this fine-grained level, the dataset is aggregated per hour. The proposed model utilizes a sigmoid activation function, and the traffic values are normalized to the [0,1] range through Min-Max normalization. During evaluation, the predicted values are rescaled to their original values and compared with the ground truth. The test data consists of traffic from the last 7 days, while all data preceding this period is designated as training data.

Two deep networks are trained using the Adam optimization technique with a mini-batch size of 32 for 100 epochs. The initial learning rate is set at 0.01 and is reduced by a factor of 10 at 50% and 75% of the total training epochs. The convolutional layers in both networks consist of 32 filters with a 3×3 size, except for the last layer, which employs 2 filters of size 3×3. The lengths of dependent sequences (p and q) are both set to 3.

Evaluation of model performance is based on the root mean square error (RMSE), which serves as the chosen metric for assessing the accuracy of predictions against the ground truth. This comprehensive approach aims to address the challenges associated with sparse cell traffic data, providing a robust framework for predicting and optimizing network resource usage over hourly intervals.

B. Overall Performance

The effectiveness of the proposed deep learning-based cellular traffic prediction method is validated through experiments conducted with two types of datasets: SMS and Call. The performance is measured using the root mean square error (RMSE) of the prediction, denoted as Proposed-F, and is presented in Fig. 3. Additionally, Fig. 3 includes the RMSE without the parametric matrix-based fusion scheme (XL_c+1 + XL_p+1), referred to as Proposed. The results demonstrate that the fusion scheme enhances performance in terms of RMSE, indicating that learning the weights of closeness and period contributes to a more accurate description of their function in traffic prediction. For comparison, three existing algorithms—Historical Average value (HA), ARIMA, and LSTM—are used as baselines, as they are widely employed in current research for traffic prediction. The RMSE values reveal that the proposed method achieves the most accurate prediction. This superiority is attributed to the collective modeling of spatial and temporal dependences among different cells through the utilization of Convolutional Neural Networks (CNNs). Notably, RMSE values on the Call dataset are relatively lower than those of the SMS dataset, as the pattern hidden in the Call dataset is more "regular" compared to the SMS dataset, as observed in Fig. 1a. This regularity makes it easier for the deep model to learn.

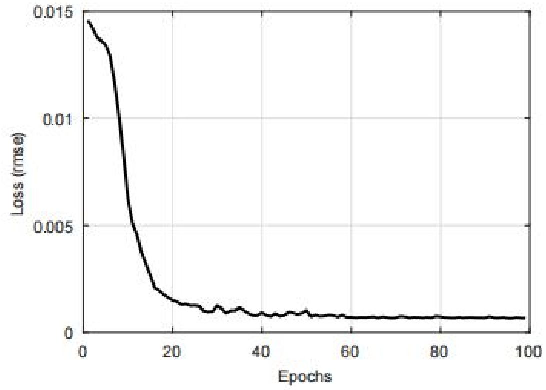


Fig. 4: The change of training loss with each epoch.

It's emphasized that real communication systems may require re-training to adapt to new incoming data. To demonstrate the convergence speed of the proposed method, Fig. 4 illustrates the training loss after each epoch. The graph shows a rapid decrease in loss during the first 20 epochs, followed by a gradual convergence to a stable status after 40 epochs. This trend indicates that the training process of the proposed method is time-efficient.

C. Prediction Results

The study presents comparisons between the predicted inbound and outbound traffic of a randomly selected cell and the corresponding ground truth values. The results are depicted in Fig. 5, showcasing a notable alignment between the predicted outcomes and the actual trends. This alignment holds true even during periods of traffic instability, notably in the time slots ranging from the 130th to the 160th. The model effectively captures and predicts peaks in both inbound and outbound traffic, demonstrating its ability to anticipate fluctuations and maintain accuracy in forecasting, even in challenging scenarios.

VIII. CONCLUSION

This study explores the interplay of spatial and temporal dependencies within traffic patterns across different cells and introduces a deep learning methodology to collectively model these dependencies for traffic prediction. Specifically, a parametric matrix-based fusion scheme is introduced to precisely characterize the influence of both spatial and temporal dependencies. The approach treats traffic data as images, enabling efficient prediction of citywide traffic dynamics. Experimental results underscore the superiority of the proposed Convolutional Neural Network (CNN)-based approach, as evidenced by its superior performance in terms of Root Mean Square Error (RMSE) compared to existing methods.

It's important to highlight that optimal performance with the proposed approach necessitates a substantial volume of training data. The study emphasizes the significance of a large and diverse training dataset for achieving the best predictive capabilities with the proposed CNN-based model.

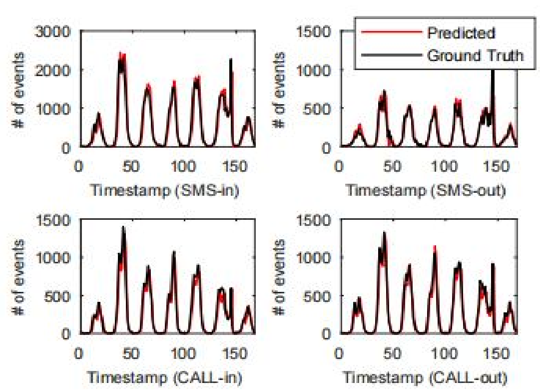


Fig.5.Prediction results of a random selected cell.

REFERENCES

[1] R. Li, Z. Zhao, X. Zhou, G. Ding, Y. Chen, Z. Wang, and H. Zhang, "Intelligent 5G: When cellular networks meet artificial intelligence," IEEE Wireless Commun. Mag., vol. 24, no. 5, pp. 175–183, Oct. 2017.

[2] N. Saxena, B. J. R. Sahu, and Y. S. Han, "Traffic-aware energy optimization in green LTE cellular systems," IEEE Communications Letters, vol. 18, no. 1, pp. 38–41, Jan. 2014.

[3] A. D'Alconzo, A. Coluccia, F. Ricciato, and P. Romirer-Maierhofer, "A distribution-based approach to anomaly detection and application to 3G mobile traffic," in IEEE Global Telecommunications Conference, Nov 2009, pp. 1–8.

[4] B. Zhou, D. He, and Z. Sun, Traffic Modeling and Prediction using ARIMA/GARCH Model. Boston, MA: Springer US, 2006, ch. 5, pp. 101–121.

[5] R. Li, Z. Zhao, J. Zheng, C. Mei, Y. Cai, and H. Zhang, "The learning and prediction of application-level traffic data in cellular networks," IEEE Trans. Wireless Commun., vol. 16, no. 6, pp. 3899–3912, Jun. 2017.

[6] J. G. D. Gooijer and R. J. Hyndman, "25 years of time series forecast ing," International Journal of Forecasting, vol. 22, no. 3, pp. 443 – 473,

[7] H. Zhang, L. Cao, and S. Gao, "A locality correlation preserving support vector machine," Pattern Recognition, vol. 47, no. 9, pp. 3168 – 3178, 2014.

[8] L. Nie, D. Jiang, S. Yu, and H. Song, "Network traffic prediction based on deep belief network in wireless mesh backbone networks," in IEEE Wireless Communications and Networking Conference (WCNC), San Francisco, CA, USA, Mar. 2017, pp. 1–5.

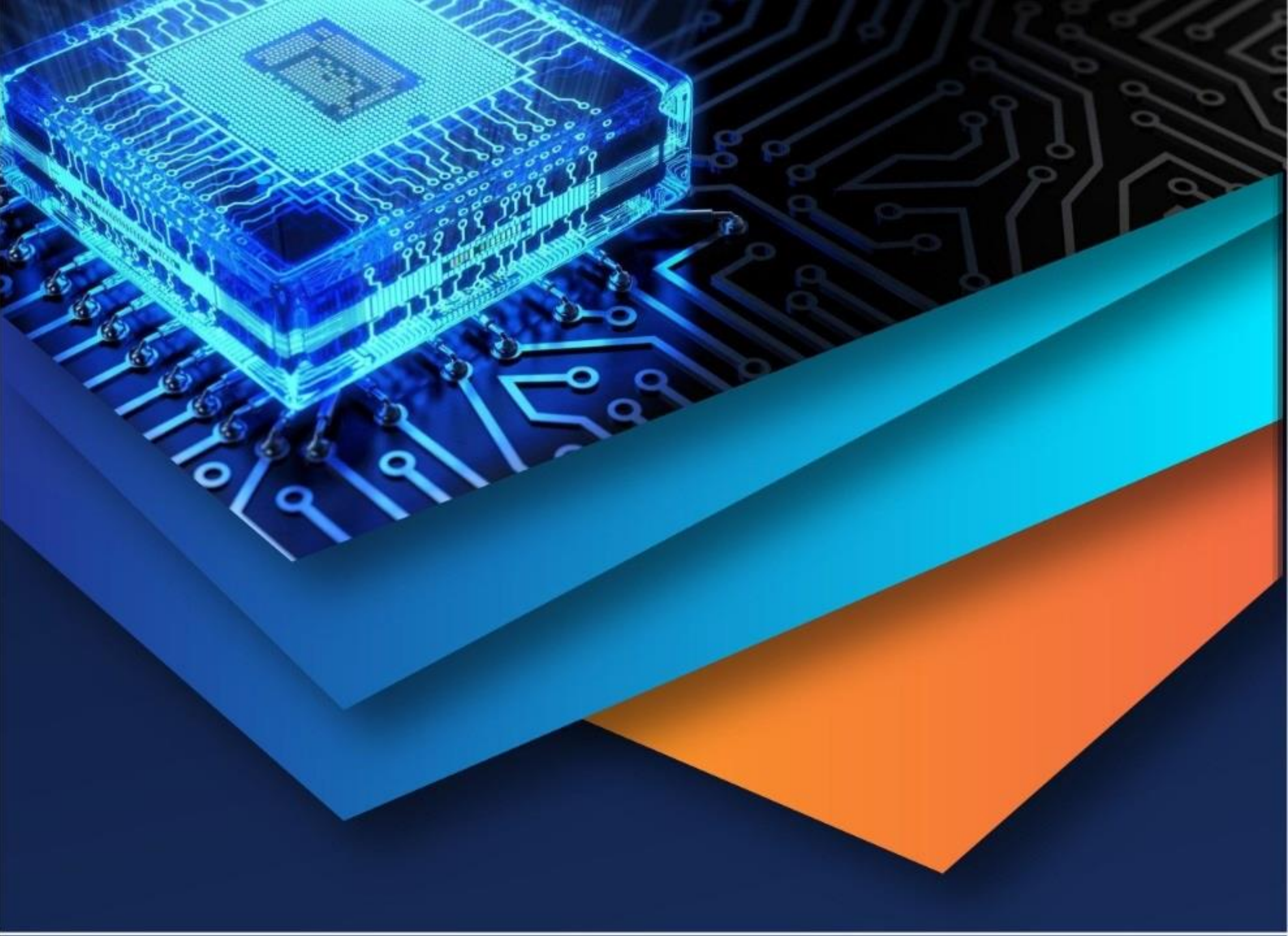
[9] J. Wang, J. Tang, Z. Xu, Y. Wang, G. Xue, X. Zhang, and D. Yang, "Spatiotemporal modeling and prediction in cellular networks: A big data enabled deep learning approach," in IEEE Conference on Computer Communications (INFOCOM), Atlanta, GA, USA, May 2017, pp. 1–9.

[10] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, May 2015.

[11] G. E. Hinton and R. R. Salakhutdinov, "Reducing the dimensionality of data with neural networks," Science, vol. 313, no. 5786, pp. 504–507, Jul. 2006.

[12] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, Hawaii, Jul. 2017.

[13] G. Barlacchi, M. De Nadai, R. Larcher, A. Casella, C. Chitic, G. Torrisi, F. Antonelli, A. Vespignani, A. Pentland, and B. Lepri, "A multi-source dataset of urban life in the city of Milan and the Province of Trentino," Scientific Data, vol. 2, p. 150055, Oct. 2015.



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY