6G Traffic Prediction with a Novel Parallel Convolutional Neural Networks Architecture and Matrix Format Method Integration

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Abstract – In the evolving world of wireless communication, sixth generation (6G) networks represent a significant leap forward. Beyond its high-speed and reliable communication, 6G integrates Artificial Intelligence (AI), making networks intelligent entities. This elevates the infrastructure of smart cities and other ecosystems. A critical factor in 6G's success is real-time traffic analysis. As 6G aims to interconnect billions of devices, it faces unprecedented traffic patterns. Practical traffic analysis ensures optimal performance, resource distribution, and energy efficiency. It also supports the network in handling vital sectors like healthcare and transportation by anticipating congestion and prioritizing crucial data. However, traditional traffic analysis techniques designed for earlier generations cannot accommodate 6G's demands. With 6G's integration of diverse technologies, understanding traffic becomes more challenging. Recent advancements have incorporated deep learning architectures, notably Convolutional Neural Networks (CNNs), for traffic analysis. While these models show potential, adapting them to 6G's specifics remains challenging. This research presents a unique parallel CNN architecture for 6G traffic prediction. It converts network data into an image using the Matrix Format Method (MFM), making it suitable for CNN processing. This innovation addresses the limitations of traditional methods and meets 6G's requirements. Compared to other models, our parallel CNN architecture highlights enhanced performance, promising increased traffic prediction accuracy. It also paves the way for improved resource allocation, energy management, and quality of service in 6G environments.

Keywords – 6G, Machine Learning, Wireless Communication, CNN, Network Traffic Analysis, Accuracy.

I. INTRODUCTION

In the rapidly transforming domain of wireless communication, the emergence of the sixth generation (6G) networks promises to be more than just a technological advancement; it heralds a seismic shift in our digital interactions. Beyond the allure of terabit-level speeds and Ultra-Reliable Low-Latency Communication (URLLC), 6G is embedding Artificial Intelligence (AI) at its very heart, ushering in a new era where networks are not mere pathways for data but intelligent entities. This combination seeks to elevate individual digital experiences and the foundational architecture of our smart cities, industries, and broader ecosystems [1]. Yet, as these networks grow in complexity and reach, their proficiency hinges on a vital ability: real-time traffic analysis. Such capability is imperative for 6G's effectiveness, ensuring it meets its lofty promises and delivers unparalleled user experiences amidst the intricacies of evolving data traffic [2].

Traffic analysis in the context of the groundbreaking 6G environment is paramount. As we transition into an era dominated by 6G networks, the vastness, complexity, and dynamism of the data traffic generated are unlike anything we've previously encountered. 6G promises to interconnect billions of devices, from smart appliances and autonomous vehicles to high-definition virtual reality systems. This exponential increase in connected devices translates to a labyrinth of data paths with unique traffic patterns [3]. Analyzing this traffic effectively is the linchpin to ensuring optimal network performance, resource allocation, and energy efficiency.

Furthermore, with 6G's emphasis on URLLC and its applications in critical sectors like healthcare, transportation, and public safety, accurate traffic analysis becomes paramount. It facilitates swift and precise decision-making, enabling the network to anticipate congestion points, mitigate potential disruptions, and prioritize data packets for mission-critical operations [4]. The prowess of 6G's transformative capabilities hinges on robust traffic analysis frameworks, underscoring its significance in shaping our connected future.

Traditional traffic analysis methodologies, built predominantly for 4G and even 5G networks, are no longer equipped to handle the sheer volume, diversity, and dynamism of 6G traffic. As 6G introduces more device types, more simultaneous connections, and greater data flow per device, there is an intrinsic need for a more sophisticated, accurate, and faster traffic analysis technique [5]. Understanding traffic patterns in real-time enables better network resource allocation, optimizes energy usage, and ensures end users' highest Quality of Service (QoS).

Furthermore, with the envisaged integration of diverse technologies such as Augmented Reality (AR), virtual reality (VR), holographic telepresence, and the Internet of Everything (IoE) in 6G environments, the traffic matrix becomes significantly more complex.

Recent advancements in network traffic analysis have seen a convergence of deep learning architectures, specifically Convolutional Neural Networks (CNNs). [6] tackled encrypted application traffic classification, integrating attention mechanisms with spatiotemporal features. Similarly, [7] applied CNN combined with an Ant-Lion Optimizer (ALO) and Self-Organizing Map (SOM), achieving remarkable results, especially with encrypted traffic. [8] brought CNNs into the Internet of Things (IoT) traffic domain, stressing the efficacy of combining CNN with Recurrent Neural Network (RNN). These approaches celebrate CNNs' hierarchical feature extraction capability, which is especially crucial for real-time traffic analysis in complex networks like 6G. While the results are promising, adapting these methods to the nuances of 6G traffic is an ongoing challenge, emphasizing the need for further tailored solutions.

In light of this, our research introduces a pioneering parallel CNN architecture specifically designed for the intricacies of 6G traffic prediction. Recognizing the unique data characteristics of 6G, we employ a transformative step, converting raw network data into an image representation via the Matrix Format Method (MFM). This approach ensures that the data's intricate patterns and nuances are retained and made more accessible to CNN processing. Such an innovation bridges the gap between traditional traffic analysis methodologies and the demands of the 6G environment. When juxtaposed with other baseline learning models, our novel Parallel CNN architecture displayed superior performance, highlighting its potential as a robust tool for real-time traffic analysis in the emerging 6G landscape. This model promises heightened accuracy in traffic prediction and sets the stage for optimizing network resource distribution energy consumption and ensuring an unparalleled Quality of Service (QoS) amidst the multifaceted traffic scenarios introduced by 6G.

The paper is organized as follows: Section 2 presents the literature review, Section 3 presents the proposed methodology, Section 4 presents the experiment analysis, and Section 5 concludes the work.

II. LITERATURE REVIEW

Network Traffic Prediction (NTP), a significant aspect of Network Traffic Management Analysis (NTMA), primarily focuses on anticipating network load and behavior. The predominant techniques historically bifurcated into statistical-based and Machine Learning (ML)-based methods [9]. While statistical methods have their merits, the surge in ML applications, particularly Deep Learning (DL) models, shows a promising trajectory for traffic prediction in evolving network landscapes.

Several studies have proposed hybrid models to enhance prediction accuracy. For instance, [10] combined the Hidden Markov Model (HMM) with Long Short-Term Memory (LSTM) for wireless network traffic prediction, demonstrating its superiority over traditional models. Similarly, [11] introduced an enhanced deep reinforcement learning algorithm for network traffic analysis and prediction, emphasizing its efficacy against other methods like CNN in specific metrics.

Moreover, with the rising complexity of 6G and its affinity with the Industrial Internet of Things (IIoT), [12] presented a self-attention traffic matrix prediction model, emphasizing its effectiveness in long-term network traffic matrix prediction in IIoT scenarios.

However, despite these advances, the literature indicates limited work, specifically on CNN-based traffic analysis for 6G networks. For example, while [13] explored the Diffusion Convolutional Recurrent Neural Network (DCRNN) for traffic load forecasting, direct applications of CNNs for 6G traffic remain underexplored. This gap underscores the need for dedicated research in this domain, motivating the focus of the current study.

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III. PROPOSED MODEL

Feature extraction by conversion of Traffic Data to Images

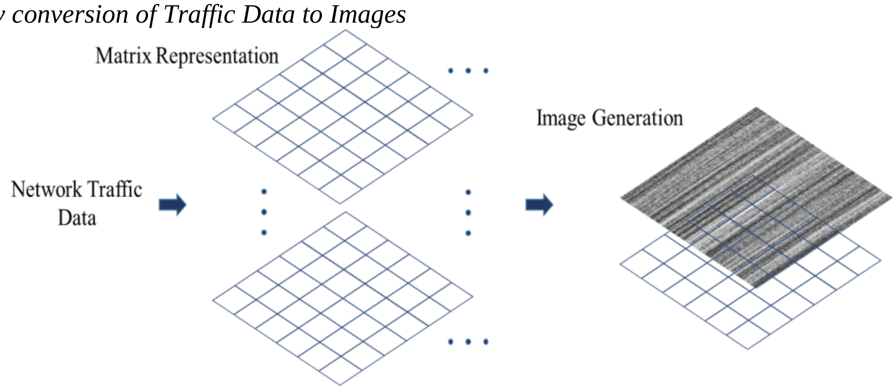


Fig 1. Network Data to Image Conversion

In the context of 6G networks **Fig 1**, Feature Extraction (FE) from traffic data adopts heightened specificity due to the network's unique characteristics. Packet length becomes pivotal in reflecting high data rate transmissions, indicating bursts of information in ultra-dense network deployments. The packet type, now possibly including newer protocols tailored for 6G, is a marker for the myriad of communication types, from augmented reality data streams to enhanced mobile broadband. Source and destination IP addresses and ports no longer indicate communication endpoints; in a 6G landscape, they could signify communication between edge-computing nodes, IoT devices, and even autonomous vehicles [14-16]. The granularity of timestamps is more refined, capturing data transitions at microsecond levels, in line with 6G's promise of ultra-reliable low latency. Payload size in 6G scenarios might indicate heavy data packets associated with holographic communications or advanced AI computations [17].

Moreover, packet flags in 6G will potentially encompass evolved signaling information, reflecting the network's dynamic topology adjustments and rapid handovers. As we journey through the nascent stages of 6G, remaining vigilant and adaptive to include any new feature will be crucial [18]. This rigorous approach to feature extraction sets the stage for an accurate transformation of 6G traffic data into image-based representations, catering to advanced CNN analyses.

Data Normalization in the Context of Traffic Data Conversion to Images

Normalization is pivotal in data processing, especially when preparing data for Machine Learning (ML) or image-based representations. The primary objective of normalization is to adjust the dataset's features to a similar scale. In the context of converting traffic data to images, this procedure is of paramount importance. Consider the different scales of features extracted from traffic data: packet lengths might range from a few bytes to several kilobytes, while timestamps might be represented as large epoch numbers. Without normalization, when these diverse scales of features are used to construct an image, a feature with larger numeric values could disproportionately influence the resulting image, masking or overshadowing the patterns and variations of features with smaller numeric values. By normalizing the features, each attribute is adjusted to a consistent scale, often between 0 and 1 or -1 and 1. This ensures that each feature contributes equally to the image construction. The resulting image thus becomes a balanced representation of all the FE, allowing for more accurate and meaningful analyses using CNNs. Normalization is a preparatory step that mitigates potential biases in the image representation and ensures the image accurately reflects all the critical facets of the traffic data.

Image Construction using the MFM

The MFM is a foundational approach to converting normalized traffic data into image representations. This method hinges on organizing the data tabularly, much like a matrix or a 2D array. In this construct, each row typically symbolizes a single packet or a network event, while each column represents a specific feature extracted from the traffic data. Imagine a scenario where you have captured multiple packets over a particular duration. You've extracted and normalized features such as packet length, packet type, source and destination IPs, and timestamps for each packet. When employing the MMF, each of these packets will be represented by a row, and its associated features will populate the columns of that row. As you accumulate rows (packets), the matrix grows vertically.

The visual outcome of this matrix, when represented as an image, resembles a grayscale image. Each cell in the matrix contains a normalized value between the chosen scale (often 0 to 1 or -1 to 1). The varying shades of gray in the resulting image denote different values within this scale. For instance, sequences of features, like time-series data of packet lengths, might manifest as gradients or patterns of grayscale shades, providing a visual narrative of how packet lengths vary over time. This matrix-turned-image then serves as a spatially coherent depiction of the traffic data. Each region or segment of the image corresponds to specific network events or patterns, making it a practical input for CNNs [19-20]. The CNNs can process this image to detect and learn spatial hierarchies and patterns, offering valuable insights into the underlying network behavior.

CNN Training on Traffic Images

Adapting CNNs to traffic images presents a novel way of studying and analyzing network traffic patterns. After converting traffic data into image representations using methods such as the MFM, the next step involves training a CNN on these generated images. CNNs, renowned for their prowess in image classification, FE, and pattern recognition, are ideally suited for this purpose.

Data Augmentation

One of the primary challenges in training ML models, including CNNs, is the potential risk of overfitting. Overfitting occurs when a model is too closely tailored to the training data, making it less effective in generalizing to new, unseen data. This is where data augmentation comes into play.

- Data Augmentation refers to artificially enhancing or expanding your dataset using various techniques to create variations of the existing data. For traffic images, the following techniques can be employed:
- Rotations: By slightly rotating the traffic images, you introduce minor variations to help the CNN learn more generalized features. This can be especially useful if specific traffic patterns or anomalies occur in various orientations.
- Zooming: Zooming in or out of an image can alter the perspective of features. This can be instrumental in making the CNN robust against variations in the size or scale of discernible patterns in the traffic data.
- Flipping: Flipping the traffic images horizontally or vertically can provide an alternative data view. This can be valuable, especially if specific network traffic patterns are direction-agnostic.
- Cropping: Randomly cropping sections of the traffic image can help focus on specific parts of the data. Cropping can introduce local variations, enabling the CNN to recognize essential features even if they appear in different regions of future input images.

Utilizing these augmentation techniques, one can significantly expand the diversity of the dataset. When a CNN is trained on such a diverse dataset, its generalization capability improves, reducing the risk of overfitting and potentially enhancing its accuracy and reliability when analyzing real-world, unseen traffic images in **Fig 2.**

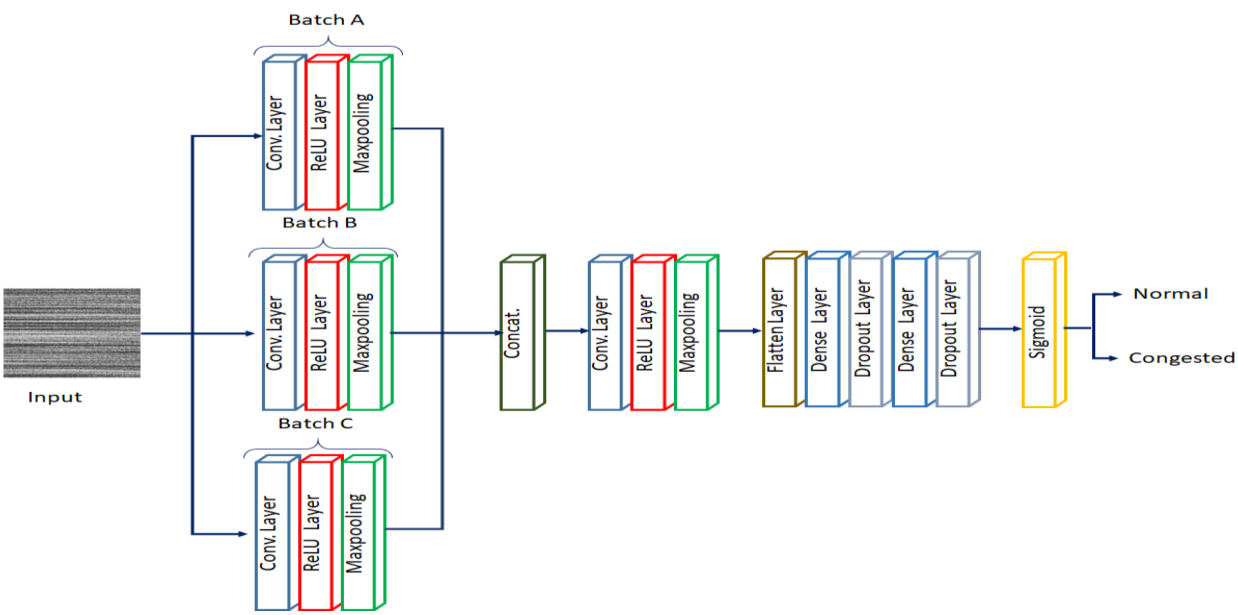


Fig 2. Parallel CNN Architecture

Proposed Parallel CNN Architecture for Training on Converted Traffic Images

In the progression of our research, once the traffic data undergoes conversion into image representations, the next critical phase encompasses the design and implementation of a CNN tailored for the unique nuances of 6G traffic patterns. Recognizing the multi-faceted nature of these traffic images, a parallel CNN architecture emerges as a logical choice [21-22]. The initial phase of the CNN begins with the Input Layer, tailored to accommodate the traffic image, designed for dimensions of 128x128 pixels.

Following this foundational layer, the architecture introduces an innovative Parallel Convolutional Branching. This parallelism comprises three distinct branches, each tailored to extract features at diverse levels of granularity:

Branch A focuses on Fine-Grained FE

This branch is essential for detecting minute variations and nuances in the traffic data, which can often be the first indicators of emerging traffic patterns or slight inconsistencies in the network. By recognizing these small-scale features, early interventions or optimizations can be made before they escalate. It starts with a convolutional layer (1A) that employs 3x3 filters, generating 32 channels. The ReLU activation function provides the necessary non-linearity, and the subsequent max-pooling layer (1A) with 2x2 pooling aids in spatial reduction.

Branch B Delves into Medium-Level FE

This intermediary branch bridges the gap between excellent details and overarching patterns. Identifying medium-scale structures or sequences in the data can recognize regular traffic patterns and be instrumental in understanding routine network behaviors and predicting future patterns based on historical and current data. This branch's convolutional layer (1B) leverages 5x5 filters, culminating in 32 channels. It also adopts the ReLU activation function, followed by a max-pooling layer (1B) with 2x2 pooling.

Branch C zeroes in on Macro-Level FE

Large-scale patterns and broad traffic behaviors fall under this branch's purview. It's crucial for understanding the overall health and performance of the network, and identifying large-scale trends aids in strategic decision-making, long-term optimizations, and comprehensive network assessments, ensuring that the network remains robust and efficient in the face of significant traffic volumes or large-scale events [23-25]. The convolutional layer (1C) utilizes 7x7 filters, resulting in 32 channels. Post this convolution, the ReLU activation function is employed, and a 2x2 max-pooling layer (1C) is integrated.

As these branches conclude their independent processing, the architecture merges their output feature maps in a Concatenation Layer, ensuring a composite feature representation from all extraction scales. After this, the network introduces a Convolutional Layer 2 that processes the concatenated map using 3x3 filters, expanding to 64 channels. The ReLU activation function is applied again, followed by a Max-Pooling Layer 2 with 2x2 pooling. The network then integrates Dense Layers to refine and interpret the extracted patterns. A flattening layer precedes the dense layers, transforming the 2D feature map into a 1D vector. The first dense layer incorporates 512 neurons with ReLU activation. To prevent overfitting, a dropout layer with a rate of 0.5 is added. This is followed by another dense layer with 256 neurons activated by ReLU and a subsequent dropout layer for enhanced model robustness. Concluding the architecture is the Output Layer. Specifically structured for binary classification - "normal" versus "congested" traffic - it comprises a single neuron with the sigmoid activation function. A definitive threshold is set at 0.5. Values below 0.5 indicate "normal" traffic, while values equal to or exceeding 0.5 signify "congested" traffic. The proposed parallel CNN architecture is meticulously crafted to discern between normal and congested traffic in 6G network environments. By leveraging the multi-scale feature extraction, it holistically analyzes the intricate patterns embedded in the 6G traffic images. Recognizing congestion in such advanced networks is crucial, given the implications for quality of service, network reliability, and user experience. With its adeptness at making nuanced distinctions, this design serves as an instrumental tool in the proactive management of 6G networks, potentially guiding interventions to alleviate congestion and maintain optimal network performance. The following algorithm presents the steps involved in the proposed 6g network traffic data analysis.

Algorithm: Traffic Data to Image & Parallel CNN Analysis for 6G Networks

Input: Raw 6G traffic data

Output: Traffic Prediction

Steps:

Traffic Data to Image Conversion:

1.1 Feature Extraction: Extract relevant features like packet length, packet type, and timestamps from 6G traffic data.

1.2 Data Normalization: Normalize the extracted features.

1.3 Matrix Construction: Convert the normalized data into a matrix format where each row corresponds to a packet.

1.4 Image Generation: Convert the matrix into a grayscale image representation.

CNN Training on Traffic Images

2.1 Data Augmentation: Introduce variations like rotations and flipping to traffic images.

2.2 Parallel CNN Training:

2.2.1 Use three parallel branches for feature extraction at distinct levels (fine-grained, medium, and macro-level).

2.2.2 Merge outputs from all branches.

2.2.3 Process through further convolutional, pooling, and dense layers.

2.2.4 Output classification using a sigmoid activation function.

Interpretation: Classify traffic as either standard or congested based on model output.

IV. EXPERIMENTAL ANALYSIS

The data was sourced from a 6G testbed network. This testbed was set up to mimic a real-world 6G environment with IoT devices, edge-computing nodes, and autonomous vehicles. It also catered to traffic from augmented reality sessions and advanced AI computations, among other typical 6G traffic sources. The data collection spanned three months, from January 1, 2023, to March 31, 2023. During this period, traffic was captured around the clock to ensure diversity in the dataset and include various network behaviors and patterns. After converting the raw traffic data into image-based representations using the Matrix Format Method:

- Number of traffic images: 5000
- Average image dimensions: 128x128 pixels (grayscale)
- Total dataset size: Approximately 3.2 GB

Given the importance of data augmentation for enhancing model performance and generalization, several techniques were applied:

- Rotations (3 variations per image)
- Zooming (2 variations per image: one zoom-in, one zoom-out)
- Flipping (2 variations per image: horizontal and vertical)
- Cropping (2 random crops per image)

This resulted in 9 augmented images per original image. Including the original images:

- Total number of images post-augmentation: 50000
- Total dataset size post-augmentation: Approximately 32 GB

The dataset was split into training and testing sets in an 80:20 ratio to ensure adequate data for model training while retaining a substantial amount for evaluation.

- Training Data: 40000 images (approximately 25.6 GB)
- Testing Data: 10000 images (approximately 6.4 GB)

The proposed CNN model is examined using a Dual Intel Xeon Platinum 8268 processor system and an NVIDIA A100 Tensor Core GPU with 40 GB memory. Accompanying the processors is 512 GB DDR4 RAM and a 2 TB NVMe SSD. The system runs on Ubuntu 20.04 LTS, using the TensorFlow deep learning framework (version 2.5) for model operations.

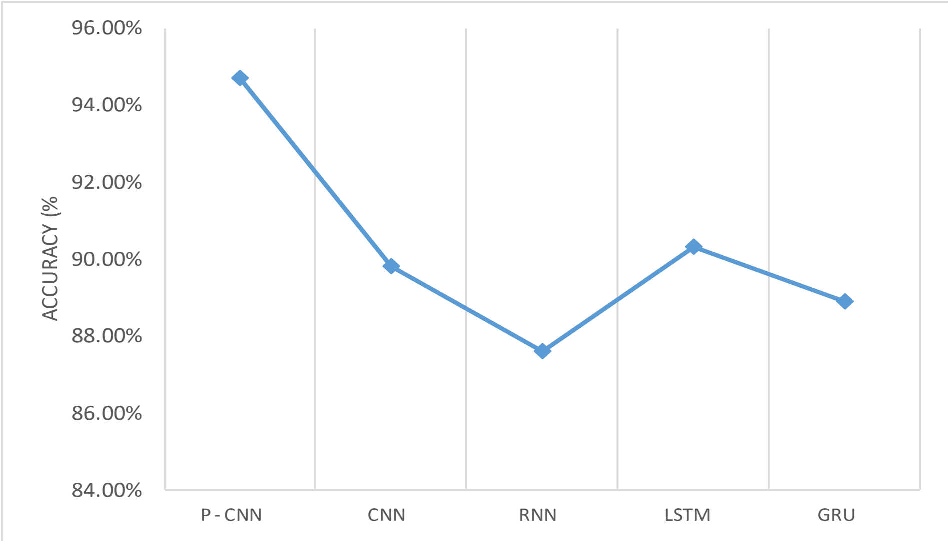
In assessing the performance of our CNN model on traffic image data, we prioritize four vital metrics. Firstly, the Accuracy metric offers a direct snapshot of the model's overall correctness, revealing the proportion of instances correctly predicted relative to the entire dataset. Second, the F1-Score, a harmonic balance between precision and recall, is invaluable, especially when facing imbalanced class distributions, as it captures the model's proficiency in accurate classifications while minimizing false positives and negatives. The AUC-ROC stands as the third pivotal metric, serving as a testament to the model's discriminative prowess by gauging its capability to differentiate between positive and negative classes. Lastly, the Loss metric, typically represented by Cross-Entropy Loss, guides us through the model's learning trajectory. It indicates the disparity between the model's predictions and the actual values, shedding light on its progression and convergence during the training phase. Together, these four metrics provide a comprehensive yet succinct evaluation of the model's efficacy in the 6G traffic image analysis domain. In evaluating the effectiveness of our proposed parallel CNN model for predicting network traffic based on converted images, we've benchmarked its performance against several established models. These include the conventional Standard CNN Model, which provides a baseline with its typical image processing capabilities. For capturing temporal sequences, we considered both the Recurrent Neural Network (RNN) and its advanced counterpart, the Long Short-Term Memory (LSTM). Additionally, we've incorporated comparisons with the Gated Recurrent Units (GRU) for their efficiency in temporal pattern recognition.

Model Performance Comparison

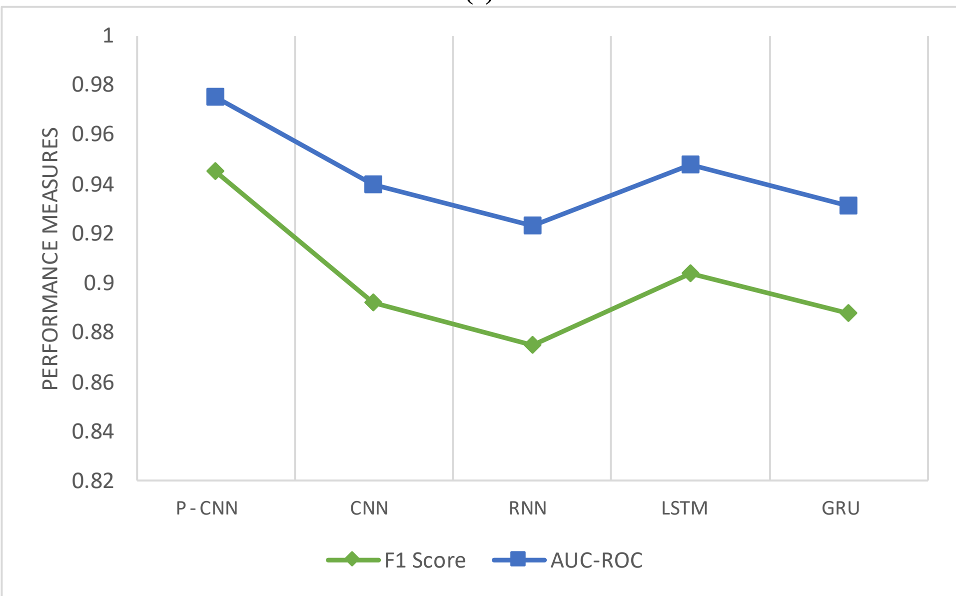
Table 1. Performance analysis for Accuracy, F1, AUC, and Cross Entropy

Model Name	Accuracy	F1 Score	AUC-ROC	Cross Entropy
Proposed Parallel CNN Model	94.7%	0.945	0.975	0.032
Standard CNN Model	89.8%	0.892	0.940	0.045
RNN	87.6%	0.875	0.923	0.051
LSTM	90.3%	0.904	0.948	0.038
GRU	88.9%	0.888	0.931	0.042

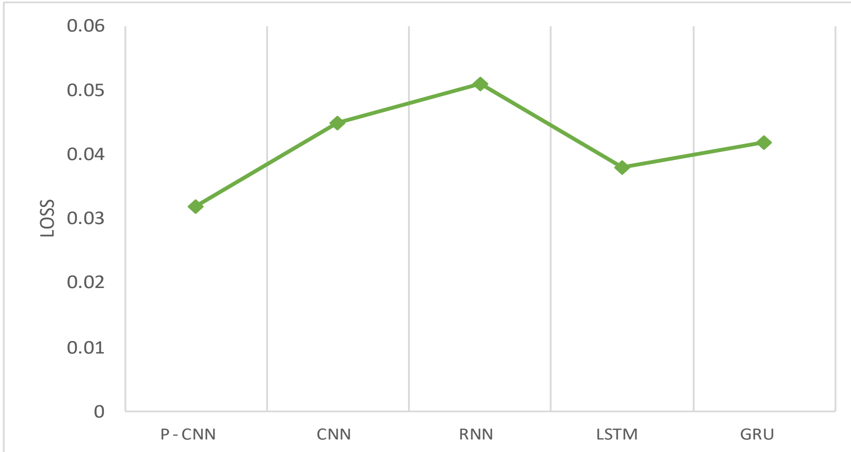
Upon examining **Table 1,** the Proposed Parallel CNN Model emerges as the standout performer across all metrics. It boasts the highest accuracy of 94.7%, suggesting an enhanced capability in classifying the converted traffic images over its counterparts. This superiority extends to the F1 Score, where the model's value of 0.945 underlines its balanced precision and recall. The AUC-ROC metric further accentuates the model's prowess, registering an impressive 0.975, indicating its superior ability to distinguish between positive and negative classes. The Proposed Parallel CNN's proficiency is also echoed in its minimal cross-entropy of 0.032, reflecting its aptitude in predicting accurate probabilities for the given classes.



(a)



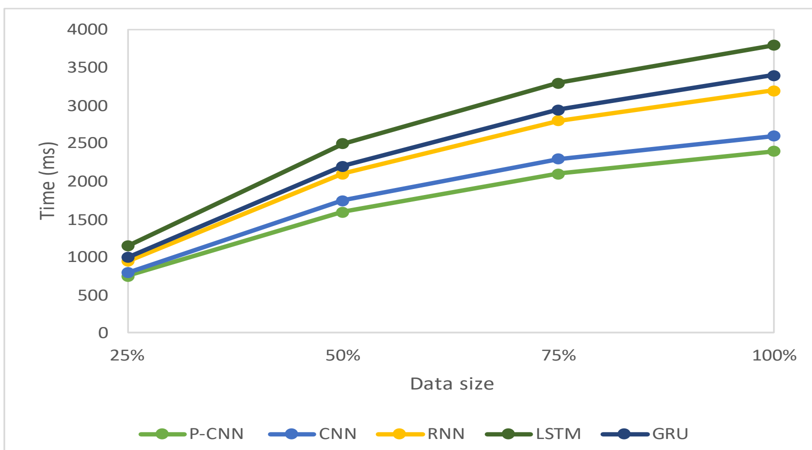
(b)



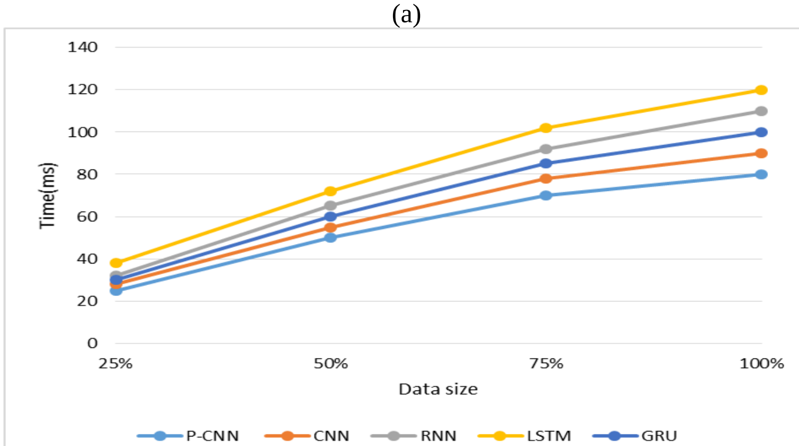
(c)

Fig 3. a)Accuracy Comparison, b) F1 and AUC comparison, and c) Cross entropy comparison

Contrasting this with the other models, the LSTM exhibits notable competitive flair, particularly regarding its cross entropy and F1 score. The standard CNN model, while lagging behind the proposed model, still posts commendable numbers, especially in accuracy and AUC-ROC. Meanwhile, RNN and GRU models display modest performance compared to the models mentioned earlier. Collectively, while each model presents its merits, the Proposed Parallel CNN Model consistently outshines the rest in this evaluation. **Fig 3 (a)-(c)** display the performance results.



(a)



(b)

Fig 4. a) Training time comparison b) Testing time comparison

Model Performance Time Scaling (ms) Based on Dataset Percentage

Table 2. Training and Testing time complexity analysis

	25%		**50%**		**75%**		**100%**	
Model Name	**Training**	**Testing**	**Training**	**Testing**	**Training**	**Testing**	**Training**	**Testing**
Proposed Parallel CNN	750	25	1600	50	2100	70	2400	80
Standard CNN	800	28	1750	55	2300	78	2600	90
RNN	950	32	2100	65	2800	92	3200	110
LSTM	1150	38	2500	72	3300	102	3800	120
GRU	1000	30	2200	60	2950	85	3400	100

Analyzing the performance time scaling of the models based on varying dataset sizes, as illustrated in **Table 2**, the Proposed Parallel CNN Model stands out with its impressive efficiency. Even at a complete dataset, it requires only 2400 *ms* for training and 80 *ms* for testing, making it the most time-efficient model among the lot. The Standard CNN Model follows closely, though at total capacity, it's slightly slower at 2600 *ms* for training and 90 *ms* for testing. RNNs scale moderately, taking 3200 *ms* to train and 110 *ms* to test at 100% dataset size. However, LSTMs are noticeably the most time-intensive, necessitating 3800 *ms* for training and 120 *ms* for testing on the full dataset. The GRU model finds a middle ground, consuming 3400 *ms* for training and 100 *ms* for testing at the maximum dataset size. While all models scale with increasing data, the Proposed Parallel CNN Model consistently displays superior time efficiency. **Fig 4 (a) and 4 (b)** illustrate comparing all the models for training and testing time complexities.

V. CONCLUSION AND FUTURE WORK

The research addresses the challenges posed by the burgeoning complexity of 6G network traffic. A parallel Convolutional Neural Network (CNN) architecture was developed in response, explicitly targeting 6G traffic prediction. This model leverages the Matrix Format Method (MFM), transforming raw network data into an image representation. Such a transformation effectively encapsulates the detailed patterns of 6G traffic, making it more accessible for CNN processing. In comparative evaluations with existing methodologies, this CNN architecture highlighted superior capabilities in analyzing real-time traffic. Beyond predictive accuracy, the model illustrates potential advancements in optimizing network resource distribution, managing energy efficiently, and ensuring consistent service quality in dynamic 6G scenarios. These findings emphasize the model's suitability in addressing the nuanced demands of an ever-evolving 6G landscape. While the initial results are promising, there is an undeniable need for continuous evolution. As 6G networks expand and their intricacies multiply, refining and adapting the current architecture becomes crucial.

Future research will focus on enhancing the model's adaptability and ensuring its relevance as 6G continues to evolve, setting a direction for subsequent advancements in network traffic analysis.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests

There are no competing interests.

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