

International Conference of Modern Systems Engineering Solutions MODERN SYSTEMS 2025

October 26, 2025 to October 30, 2025 - Barcelona, Spain

“Development of a WebRTC-based Video Calling Application to predict Quality of Service Patterns Using an Artificial Neural Network”

Ph.D Carlos Moreno. UCV, Venezuela
carlosmanuel.moreno.ucv@gmail.com

Ing. Ezequiel Frias. UCV, Venezuela
ezequieljfrias20@gmail.com

Ph.D. Vinod Kumar Verma. SLIET, India.
vinod5881@gmail.com

PhD. Eric Gamess. JSU, USA
egamess@jsu.edu



**METAOIT
Special
Track**



Carlos Moreno received his Ph.D. in Telecommunications and Computer Science from **Telecom SudParis** jointly with the **University of Paris VI – Pierre et Marie Curie**, France, in 2009. He completed a **Postdoctoral Research Fellowship** funded by the **Carolina Foundation** of Spain at the **Polytechnic University of Madrid**, Spain, in 2022. He earned a **Master's Degree in Big Data & Business Intelligence** from **Next Educación** in collaboration with the **University Isabel I**, Spain, in 2024. He holds an **MBA** from **IESA**, **Venezuela** (2017). He also obtained both a **Specialist** and a **Master's Degree in Data Networks** from the **Central University of Venezuela** (2001 and 2005). He graduated as an **Electronics Engineer** from the **Simón Bolívar University**, Venezuela, in 1998. He is currently Professor at **Central University of Venezuela** and Teacher in Collaboration with **Universidad Internacional de La Rioja – UNIR** (La Rioja, Spain), **OBS Business School** (Barcelona, Spain) and **NextEducación** (Madrid, Spain)





PhD. Carlos Moreno

Video and audio
over IP
networks, QoS,
Cibersecurity.
Big Data, IoT
and AI



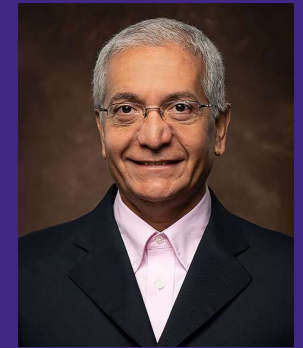
Eng. Ezequiel Frias.

Python and
Javascript
Developer. AI
architectures.
QoS in IP
networks.



PhD. Vinod Kumar
Verma

Big Data, IoT, AI,
Sensor
Networks,
Trustworthiness,
Cibersecurity



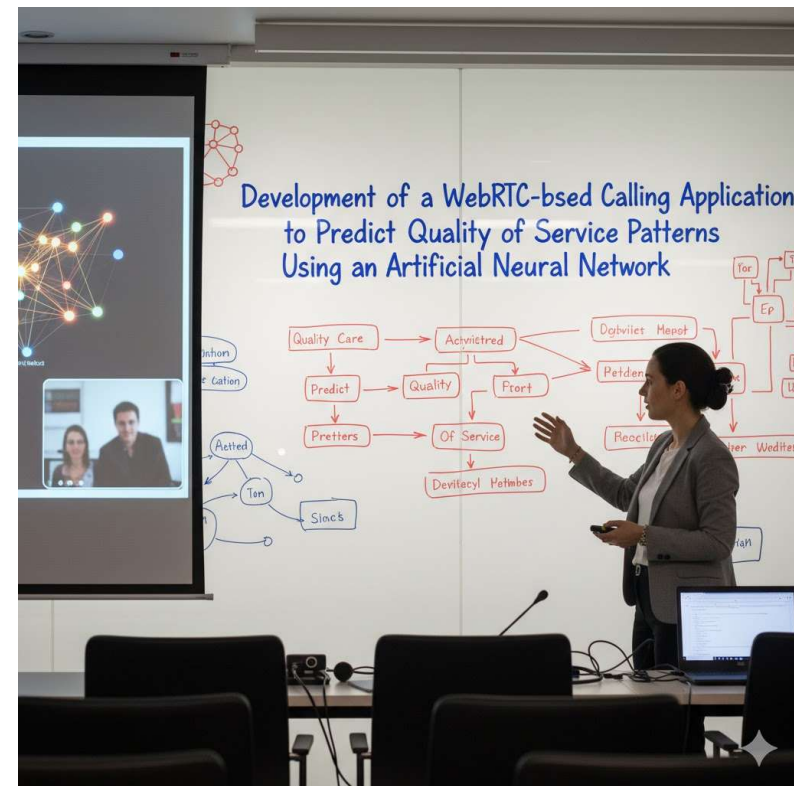
PhD. Eric Gamess

IP Networks,
IPv6,
Cibersecurity,
VANET, SDN,
SCADA



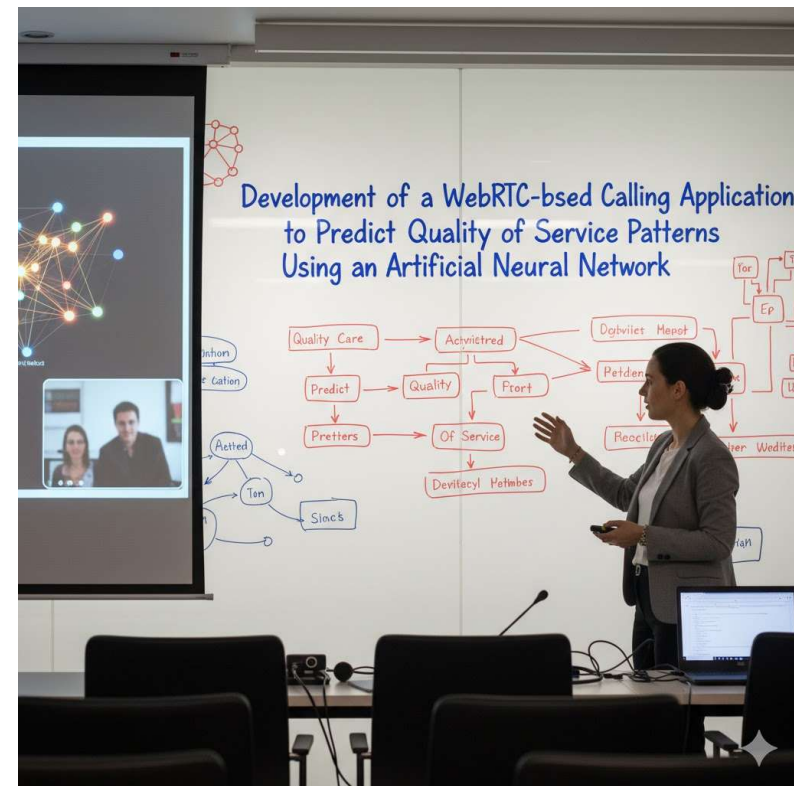
Outline

- **Motivation**
- **State of the art**
 - ✓ WebRTC studies without IA
 - ✓ WebRTC studies with IA
- **Problem formulation**
 - ✓ Research questions
 - ✓ Dissertation context
- **Methodology**
 - ✓ Description of scenarios
 - ✓ Development of neural network
 - ✓ Evaluation of the neural network
 - ✓ Prediction of QoS indicators
- **Results and analysis**
- **Conclusion and future work**
- **Questions and answers**



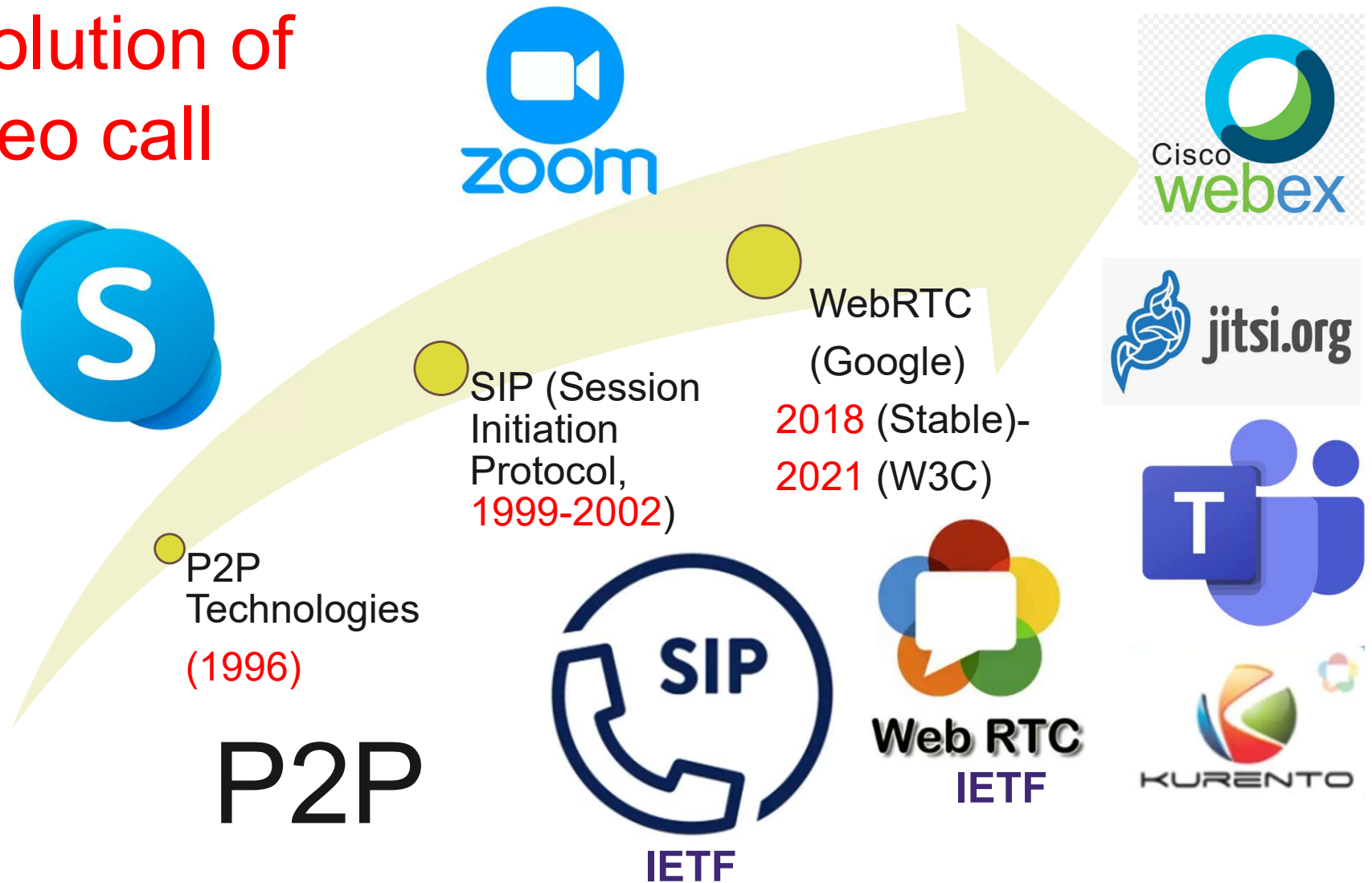
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Motivation

Evolution of video call



Evolution of AI in video calls

QoS

Jitter
Latency
Packet Loss
Throughput

QoE

-MOS
- Call
Completion
Ratio

- Lineal
Regression
- SVM
- Decision
Trees

- Supervised
Machine
Learning
(2015-2018)

- CNN
- LSTM

Deep
Learning,
(2019-2022)

QoE

- MOS
- PSNR
- SSIM

Deep Learning
In WebRTC

-Reinforcement
Learning

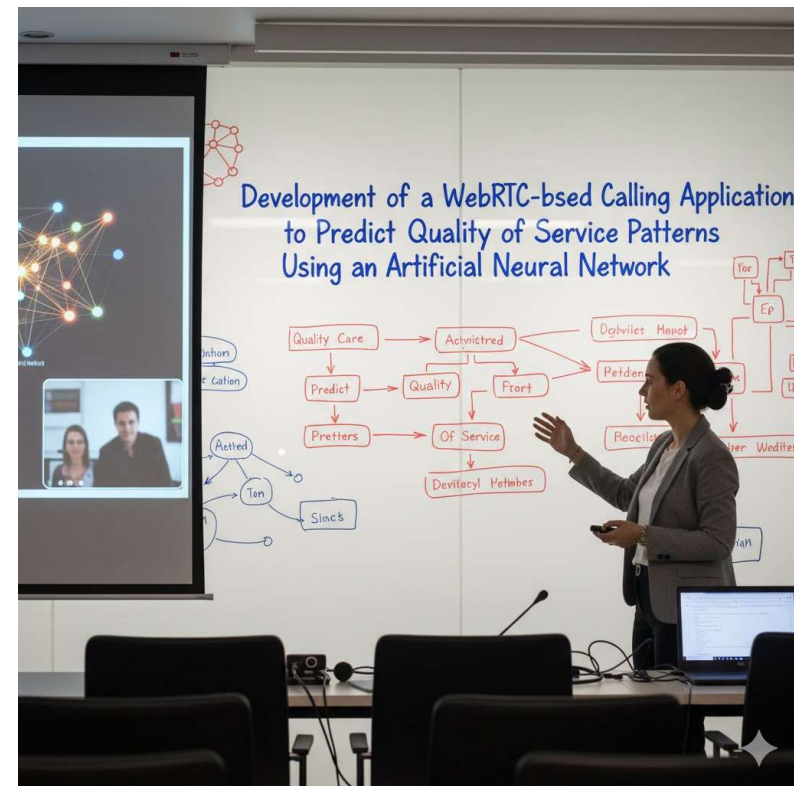
-Hybrid Models
-Dynamic
Adaptation of
WebRTC (bitrate,
resolution, FEC)
-Experimental
models: attention,
transformers

(2023-now)



Outline

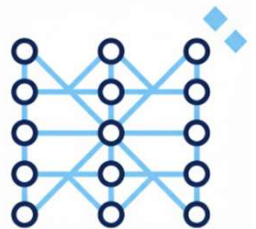
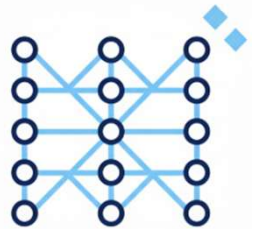
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State of the art

Prediction in non-WebRTC with Machine Learning / Deep Learning

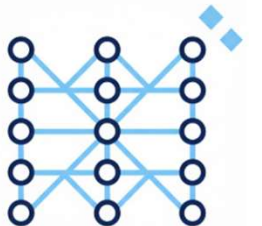
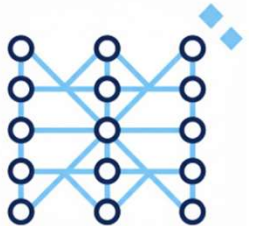
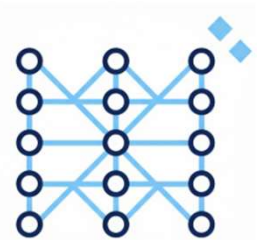
- S. Ness, V. Eswarakrishnan, H. Sridharan, V. Shinde, N. Venkata Prasad Janapareddy, and V. Dhanawat, “Anomaly Detection in Network Traffic Using Advanced Machine Learning Techniques”, IEEE Access, vol. 13, pp. 16133–16145, August 2025, doi: 10.1109/ACCESS.2025.3526988.
- Y. Wang, Z. Jia, X. Zhang, B. Shao, H. Wang, and X. Xing, “TAQ-GRNN: A Topology-Aware QoS Prediction Model Based on Gated Recurrent Neural Networks”, 2024 IEEE 13th Data Driven Control and Learning Systems Conference (DDCLS 2024), August. 2024, pp. 303-308, doi:10.1109/DDCLS61622.2024.10606915.
- M. Di Mauro, G. Galatro, F. Postiglione, W. Song, and A. Liotta, “Evaluating Recurrent Neural Networks for Prediction of Multi-Variate Time Series VoIP Metrics”, 2024 22nd Mediterranean Communication and Computer Networking Conference (MedComNet 2024), Nice, France, 2024, pp. 1-8, doi: 10.1109/MedComNet62012.2024.10578296.



State of the art

Prediction in non-WebRTC with Machine Learning / Deep Learning

- W. A. Aziz, I. I. Ioannou, M. Lestas, H. K. Qureshi, A. Iqbal, and V. Vassiliou, “Content-Aware Network Traffic Prediction Framework for Quality of Service-Aware Dynamic Network Resource Management”, IEEE Access, vol. 11, pp. 99716–99733, August 2023, doi: 10.1109/ACCESS.2023.3309002.
- Z. Wu, Y.-N. Dong, X. Qiu, and J. Jin, “Online Multimedia Traffic Classification from the QoS Perspective Using Deep Learning”, Computer Network, vol. 204, pp. 1–13, Elsevier, January 2022, doi: 10.1016/j.comnet.2021.108716.
- P. Zhang, J. Ren, W. Huang, Y. Chen, Q. Zhao, and H. Zhu, “A Deep-Learning Model for Service QoS Prediction Based on Feature Mapping and Inference”, IEEE Transactions on Services Computing, vol. 17, no. 4, pp. 1311–1325, August 2024, doi: 10.1109/TSC.2023.3326208.



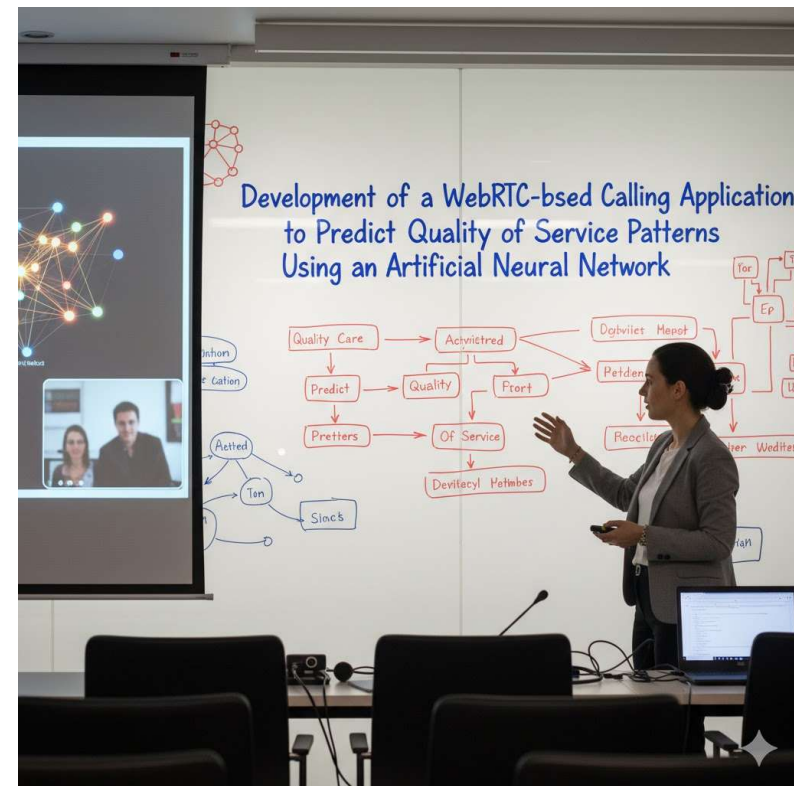
State of the art

Prediction in WebRTC with Machine Learning / Deep Learning

- “Optimizing RTC Bandwidth Estimation with Machine Learning”, <https://engineering.fb.com/2024/03/20/networking-traffic/optimizing-rtc-bandwidth-estimation-machine-learning/> 
- K. Sakakibara, S. Ohzahata, and R. Yamamoto, “Deep Learning-Based No-Reference Video Streaming QoE Estimation Using WebRTC Statistics”, 2024 IEEE International Conference on Artificial Intelligence in Information and Communication (ICAIIIC 2024), February 2024, pp.1-7, doi: 10.1109/ICAIIIC60209.2024.10463278 
- G. Bingol, “Advancing Video Communication: From WebRTC Quality Prediction to Green Applications”, Ph.D. Dissertation, Department of Electrical and Electronical Engineering, University of Cagliari, Cagliari, Italia, 2025. 

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Problem formulation

□ Research questions

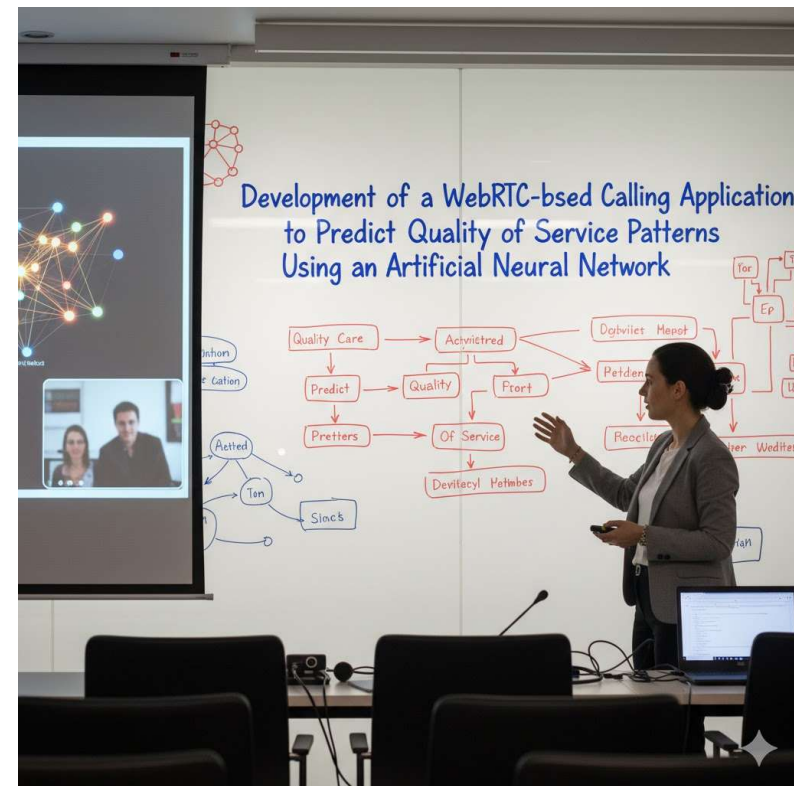
- Question 1: Which QoS metrics can be considered to measure, analyze, and predict QoS patterns?
- Question 2: Which specific type of neural network predicts better QoS in a WebRTC-based video call?

□ Context

- Universidad Central de Venezuela has research lines related to: Effect of cybersecurity over QoS in videocalls with WebRTC
- SLIET has research lines related to IoT , Cloud Computing, Trustworthiness, Machine Learning and Deep Learning
- JSU has research lines related to Big Data and Cibersecurity

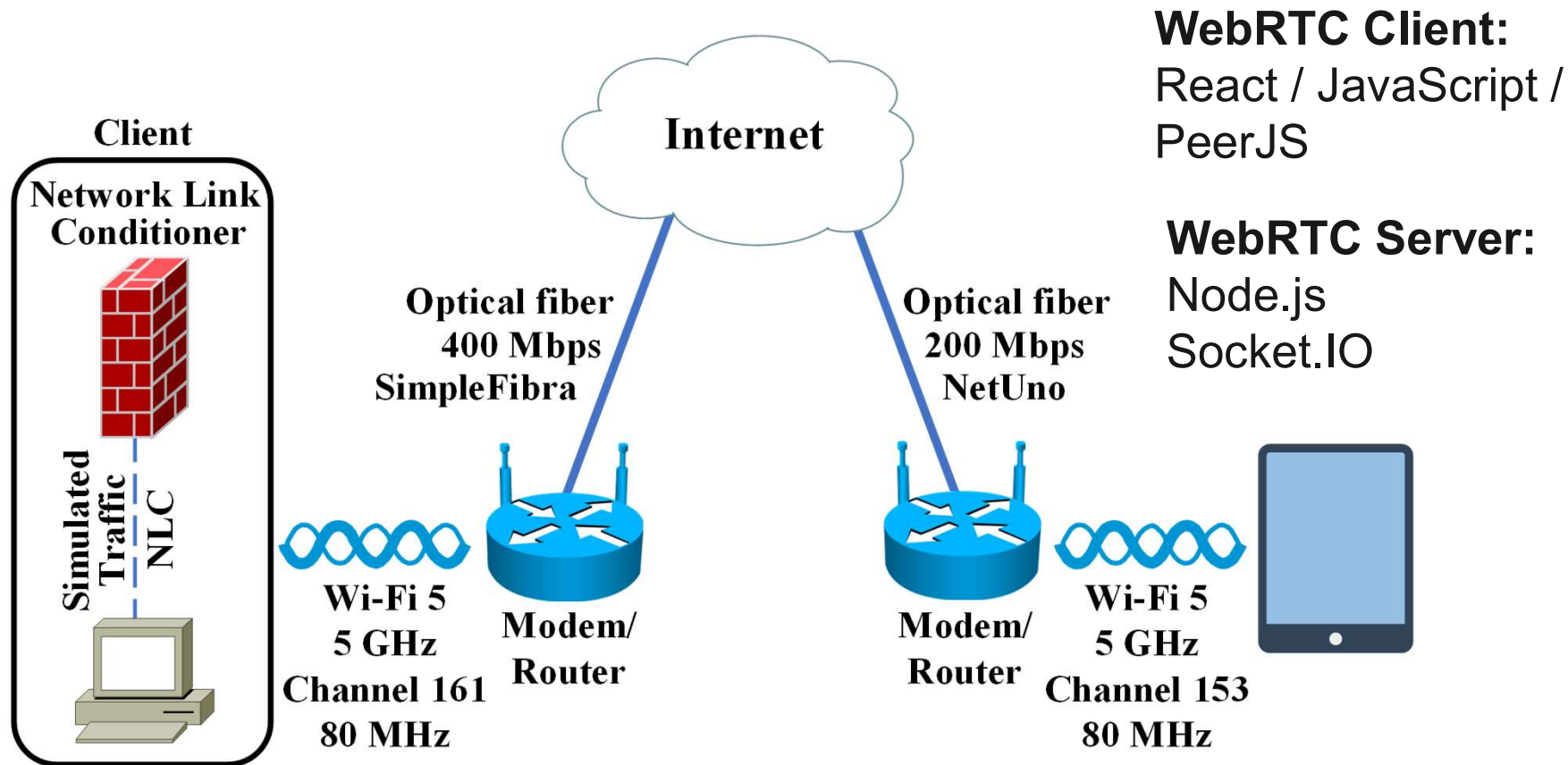
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Description of Scenarios

Testbed with 4 scenarios



Critical QoS parameters in WebRTC: latency, jitter, packet loss rate

Description of Scenarios

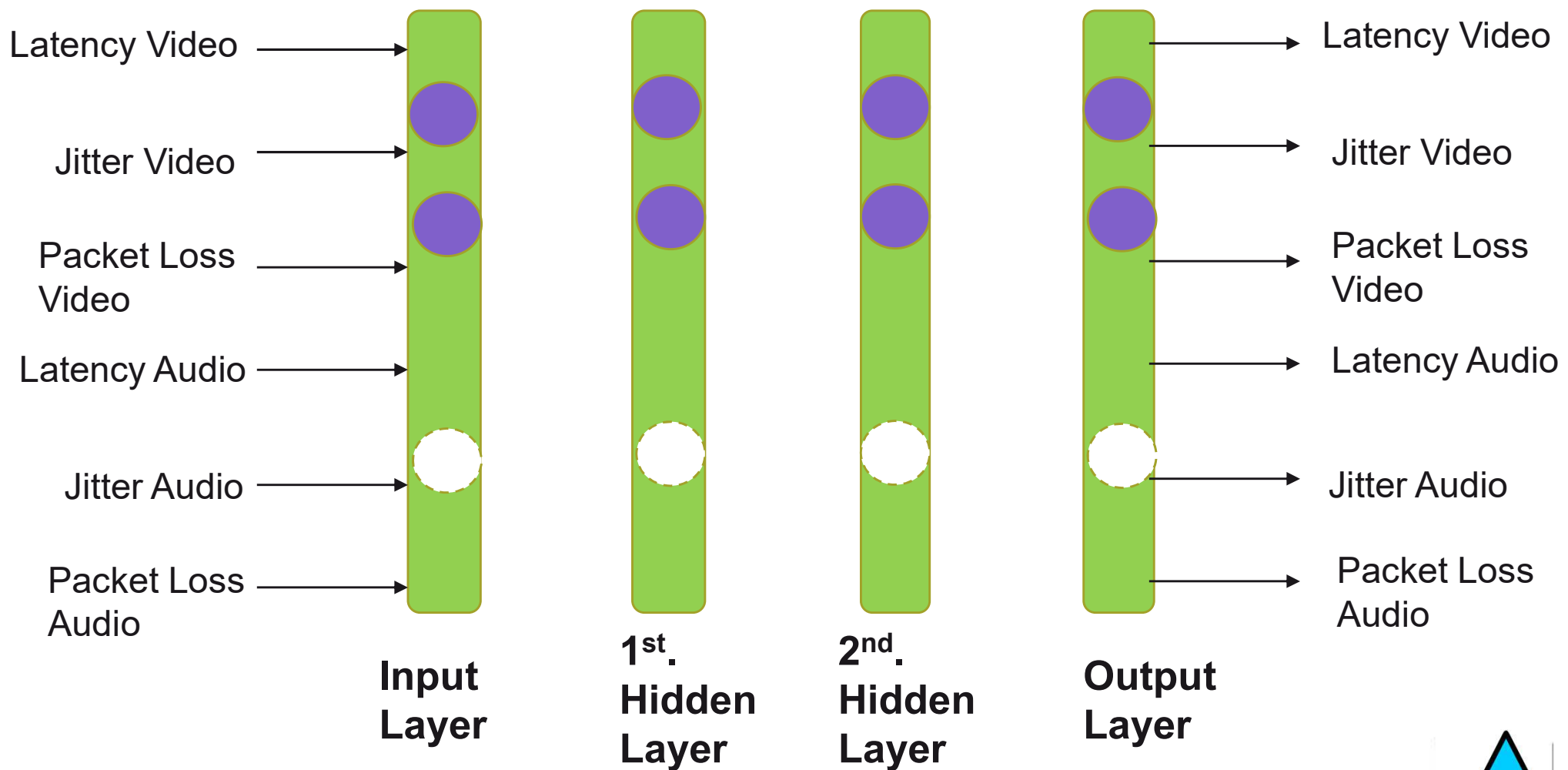
4 Scenarios

Scenario	Bandwidth	Latency	PLR	Description
(1) Acceptable Quality	50 Mbps	20 ms	0%	Acceptable
(2) Moderate Degradation	2 Mbps	100 ms	3%	Congestion
(3) Critical Quality	0.8 Mbps	200 ms	10%	Deficient
(4) Extreme Conditions	0.3 Mbps	500 ms	20%	Degraded

Tool: Network Link Conditioner (scenarios produced by Apple Laptop)

Development of Neural Network

Architecture of Neural Network



Evaluation of Neural Network

Architecture of Neural Network

Hyperparameter	GRU-1	GRU-M	LSTM-1	LSTM-M
Output (steps)	1	30	1	30
LSTM Layers	2	2	2	2
Neurons per Layer	128	128	128	128
Optimizer	Adam	Adam	Adam	Adam
Learning Rate	0.001	0.001	0.001	0.001
Epochs	12	11	32	25
Batch Size	16	16	16	16

Training Set (80%) for the 4 scenarios (1 hour all scenarios)

Testing Set (20%) for each scenario (1 call of 5 minutes per scenario)

GRU-1

**Gated Recurrent
Unit**

Single Output

GRU-M

**Gated Recurrent
Unit**

Multiple Output

LSTM-1

**Long Short-Term
Memory**

Single Output

LSTM-M

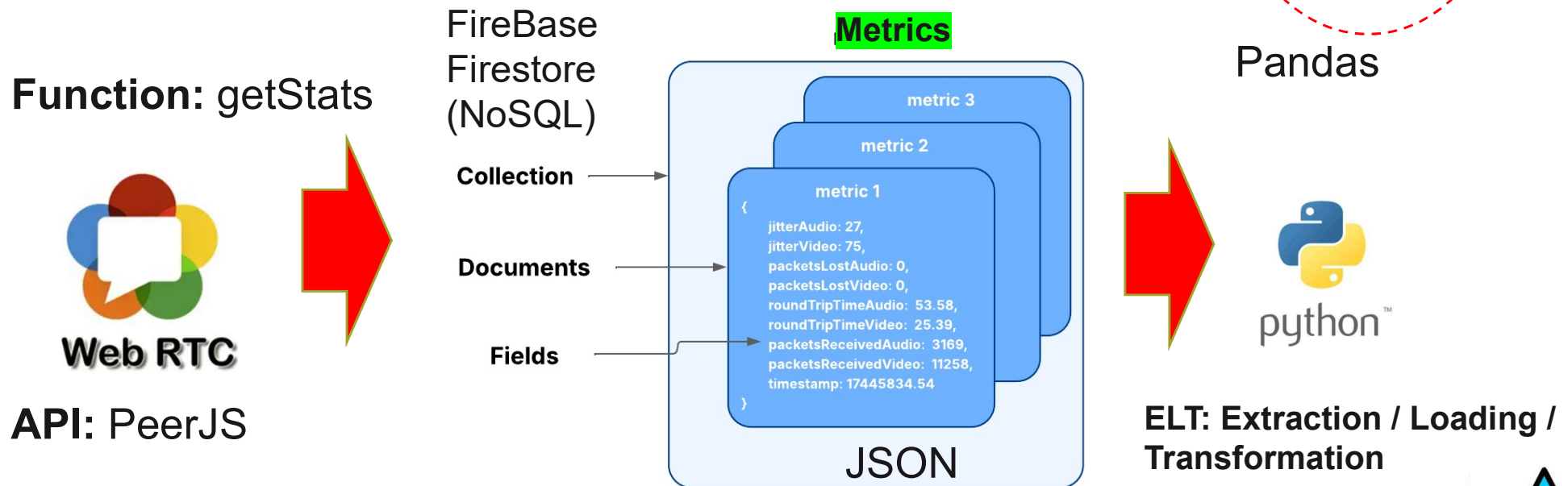
**Long Short-Term
Memory**

Multiple Output

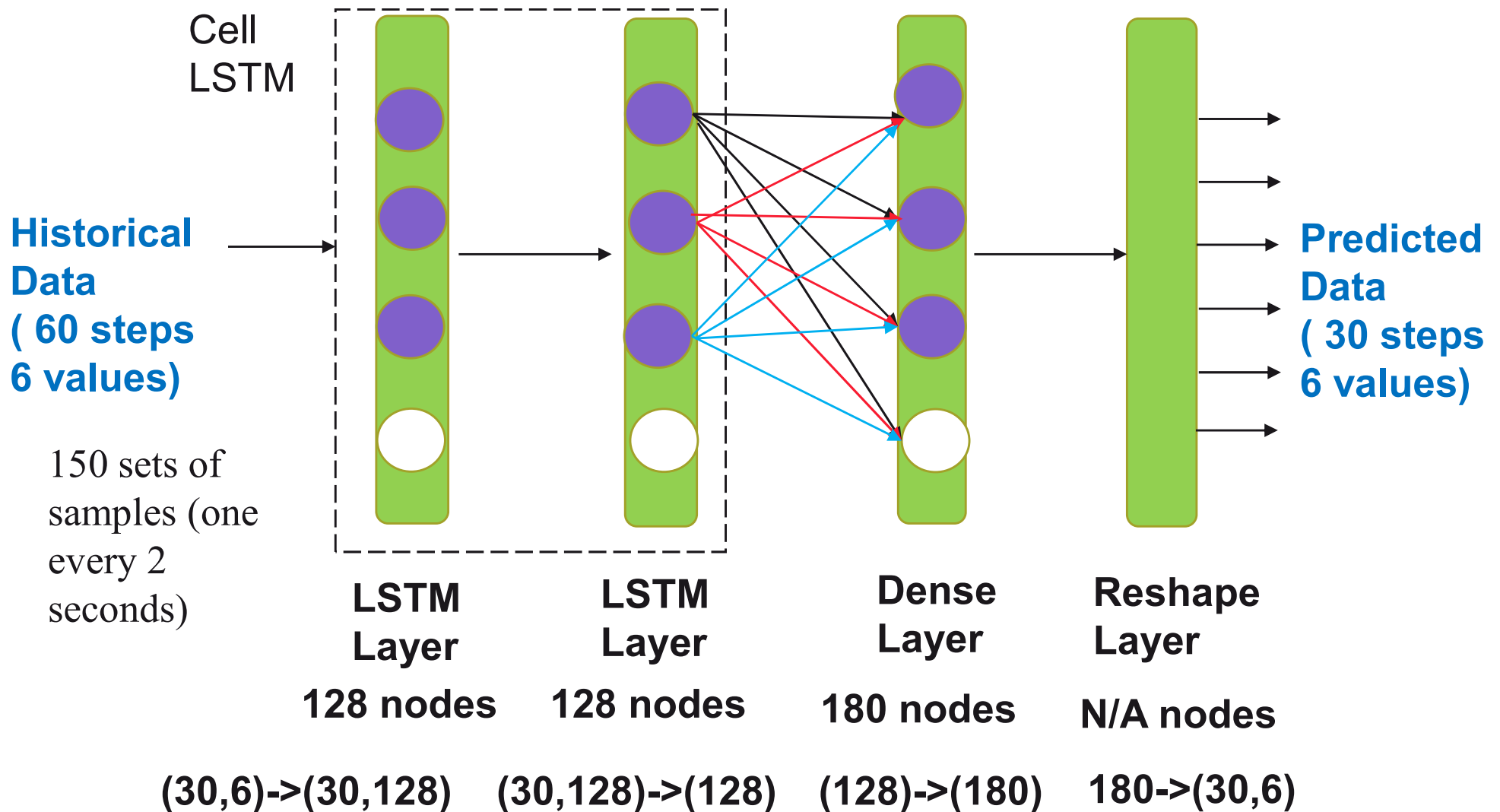
Evaluation of Neural Network

Architecture of Neural Network

Hyperparameter	GRU-1	GRU-M	LSTM-1	LSTM-M
MAE (Mean Absolute Error)	0.1154	0.1365	0.0601	0.1205
MSE (Mean Squared Error)	0.0424	0.0540	0.0098	0.0418
RMSE (Root Mean Squared Error)	0.2059	0.2324	0.0994	0.2044

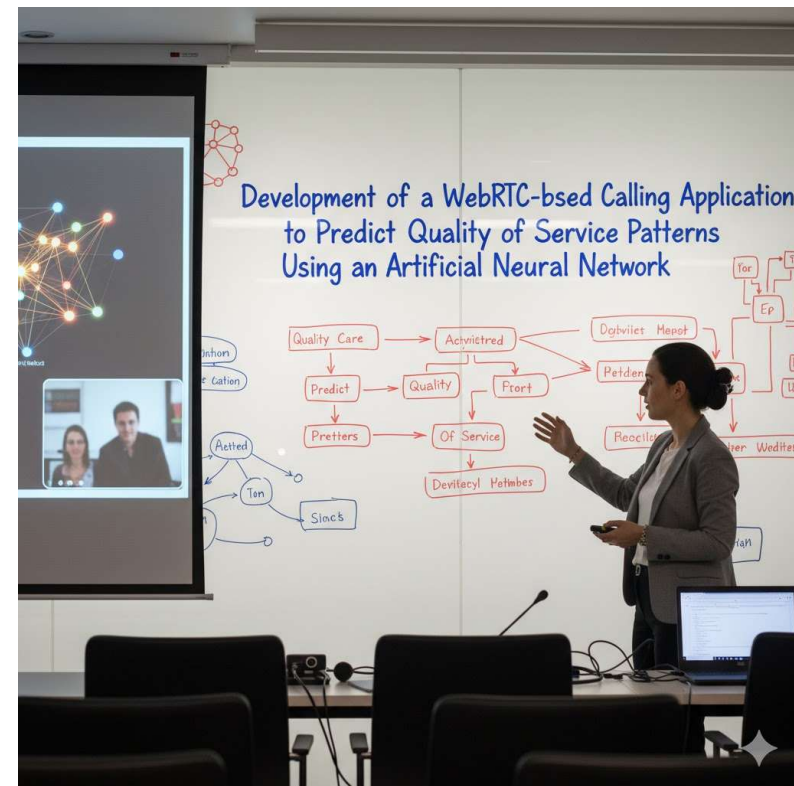


Prediction of QoS indicators



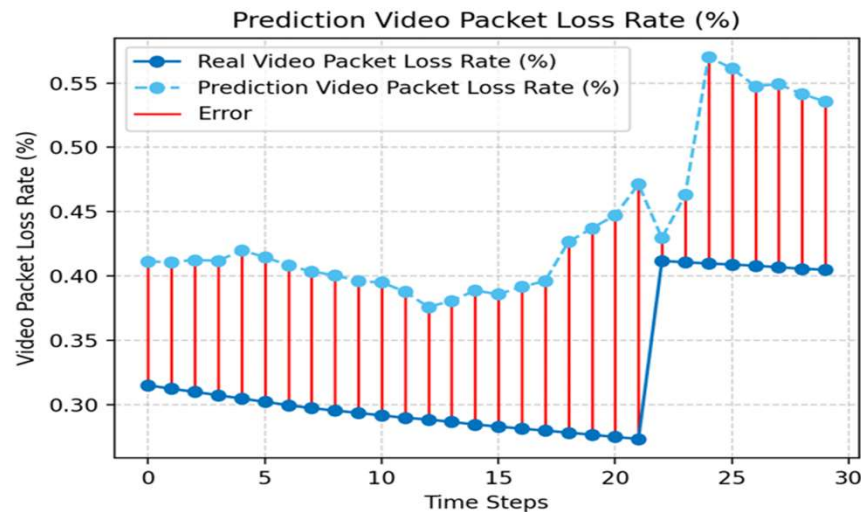
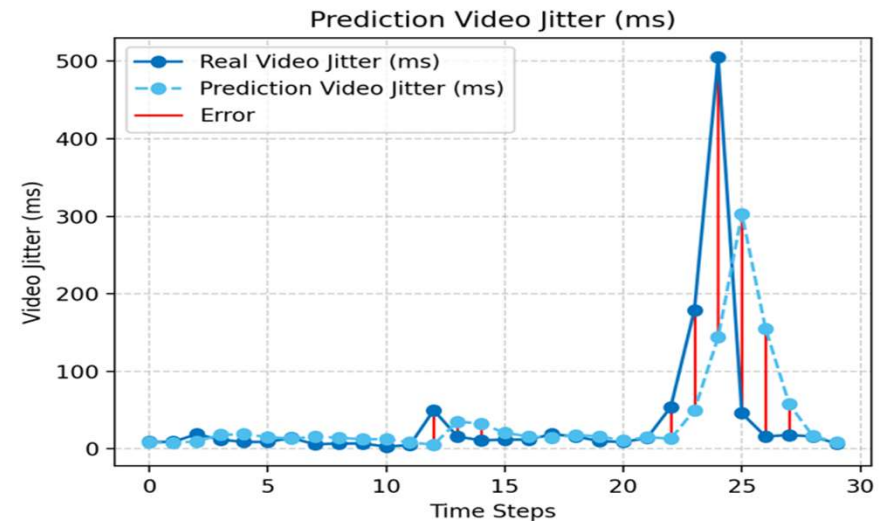
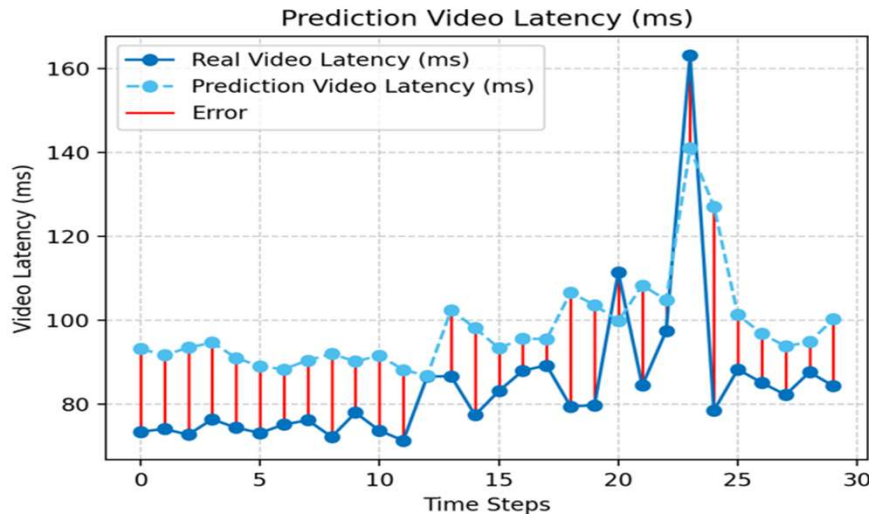
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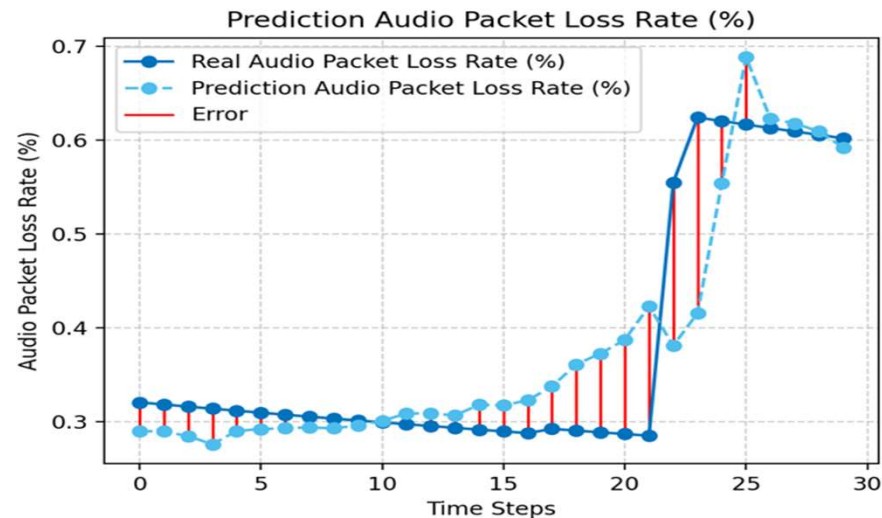
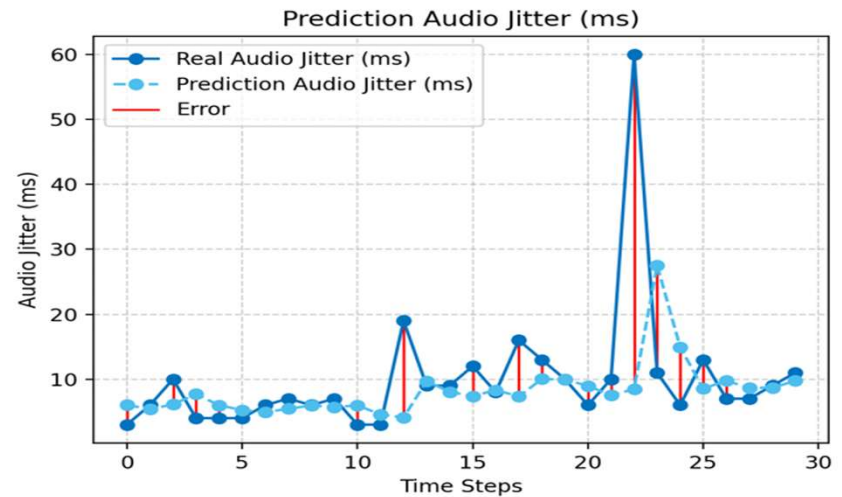
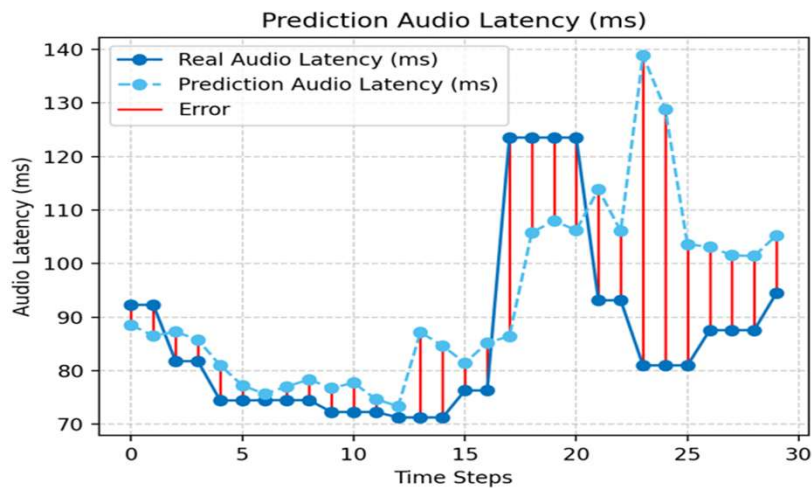
Results and analysis

Scenario 1 - Acceptable Quality (Video)



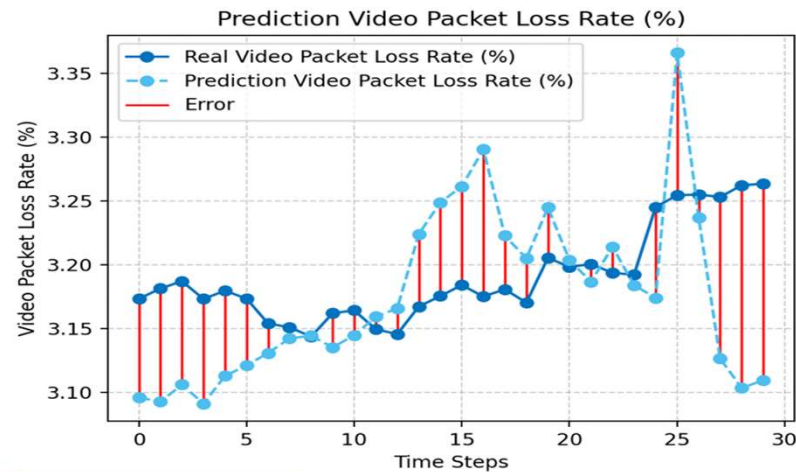
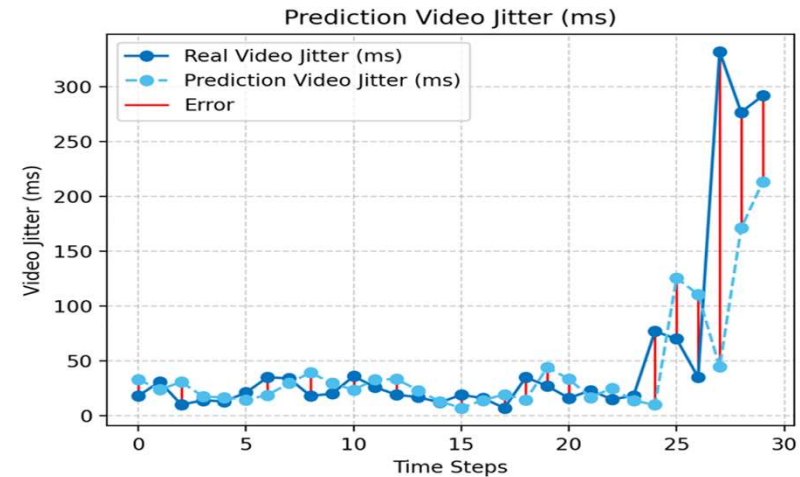
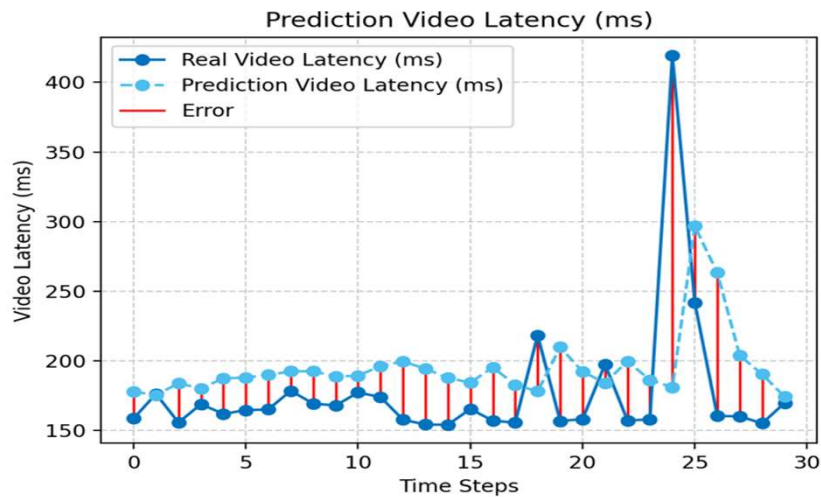
Results and analysis

Scenario 1- Acceptable Quality (Audio)



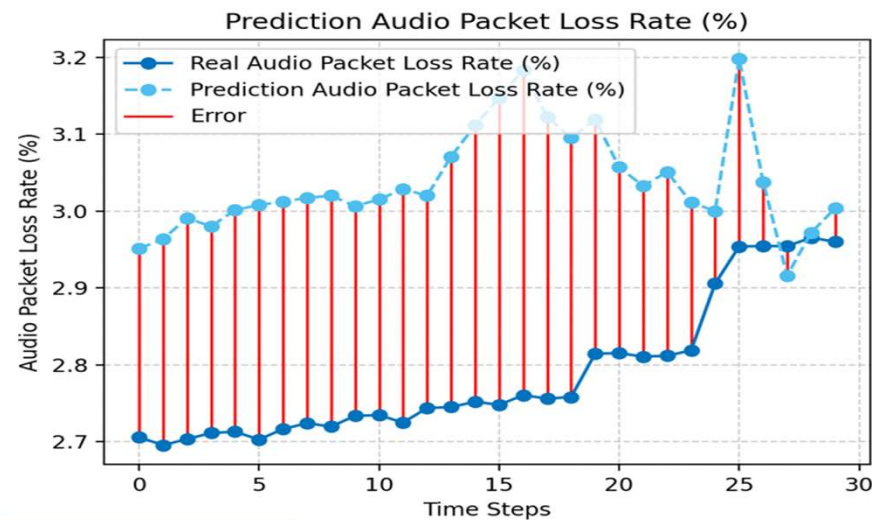
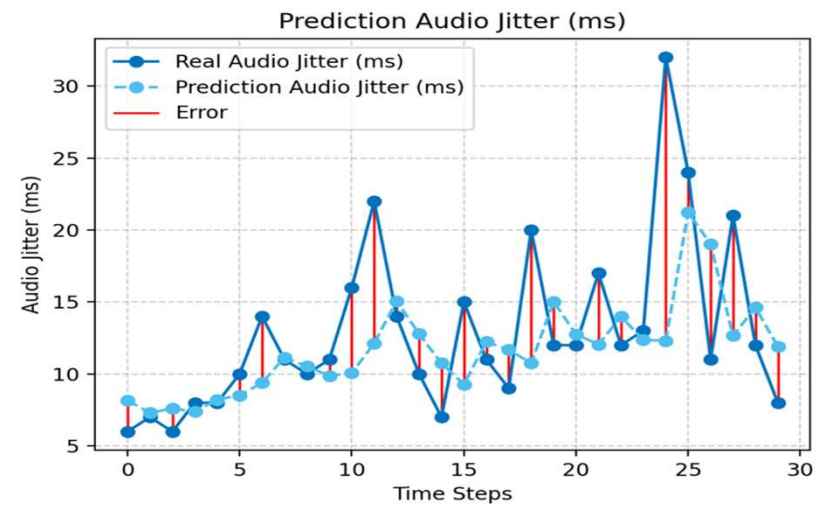
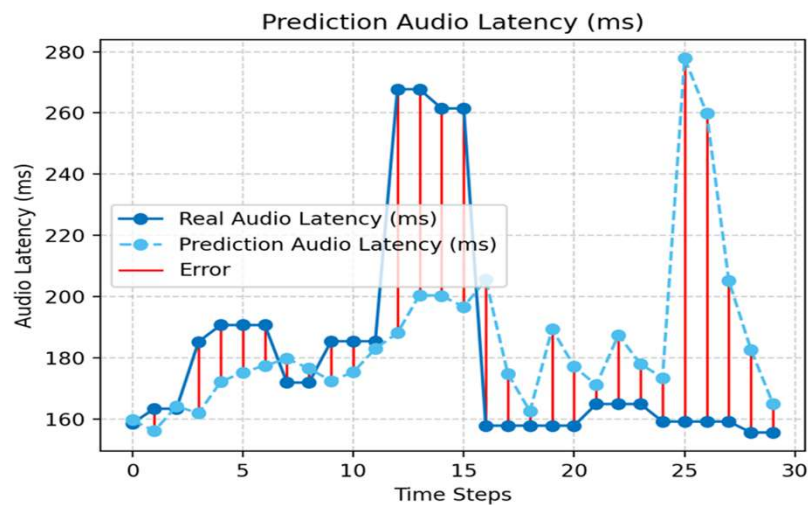
Results and analysis

Scenario 2 - Moderate Degradation (Video)



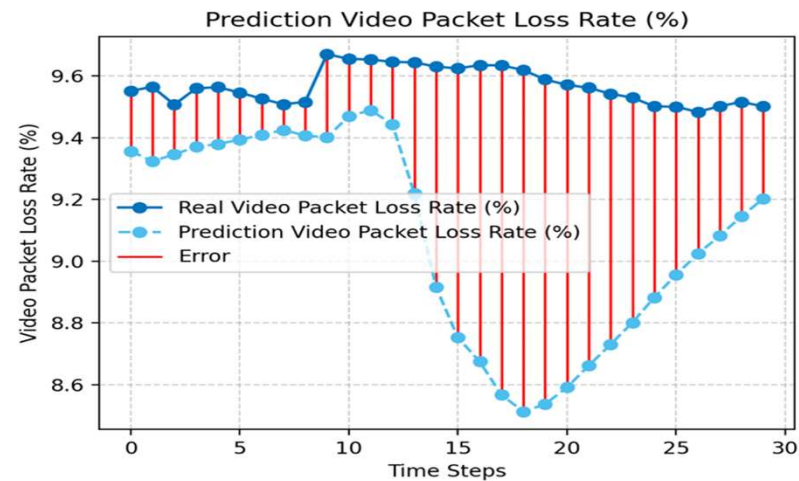
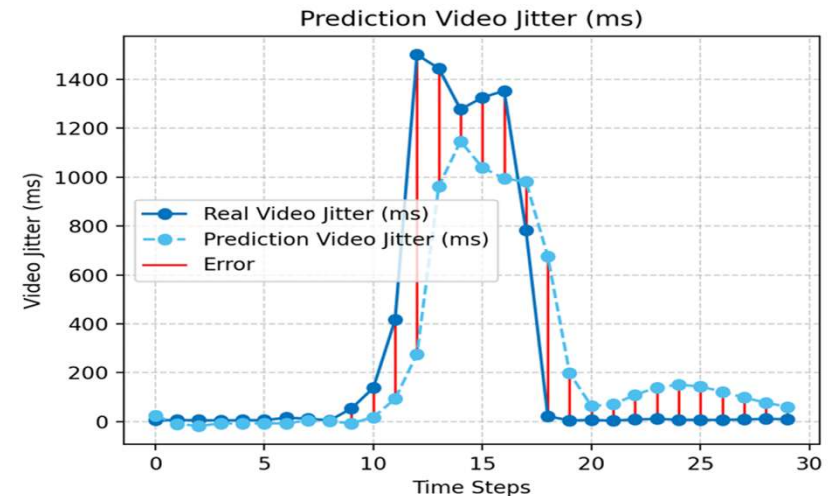
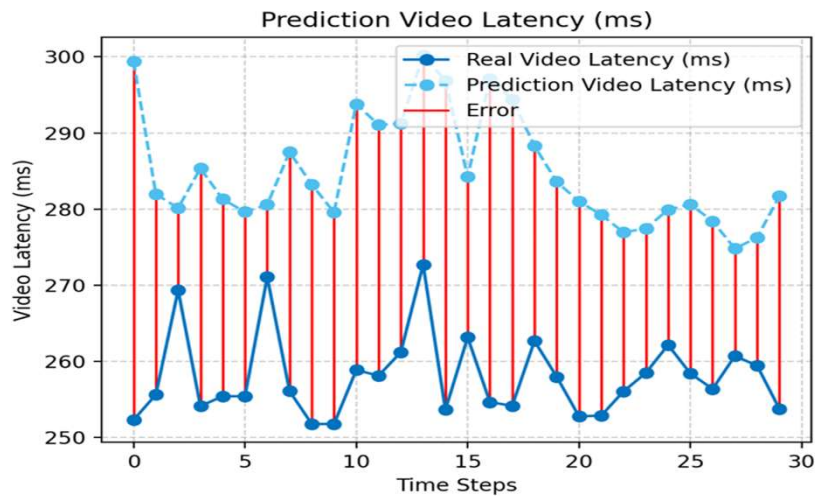
Results and analysis

Scenario 2 - Moderate Degradation (Audio)



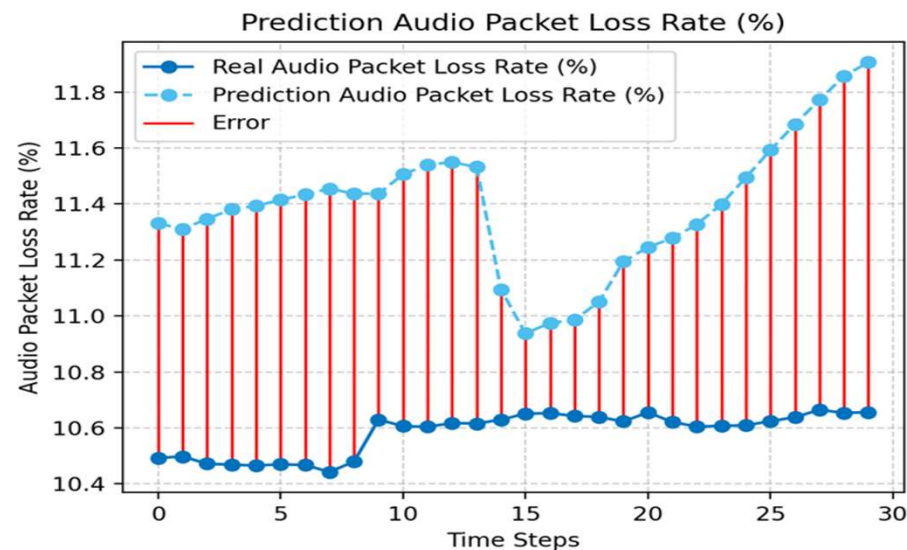
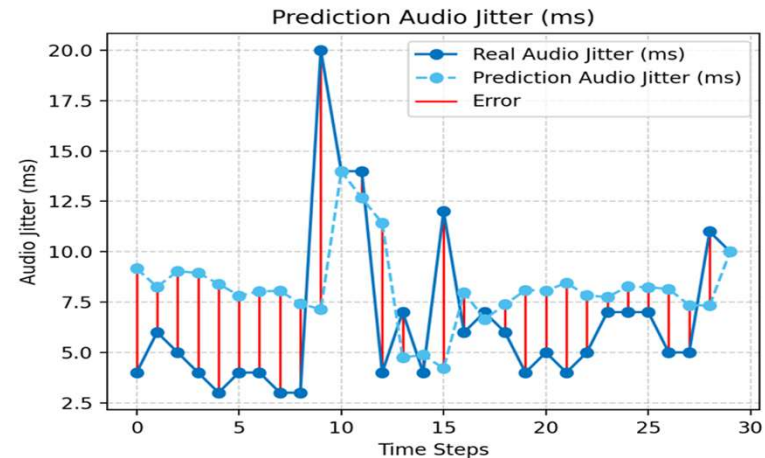
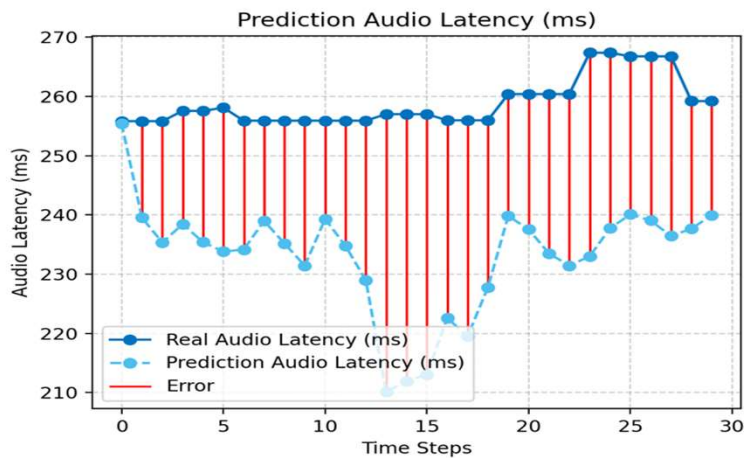
Results and analysis

Scenario 3 - Critical Quality (Video)



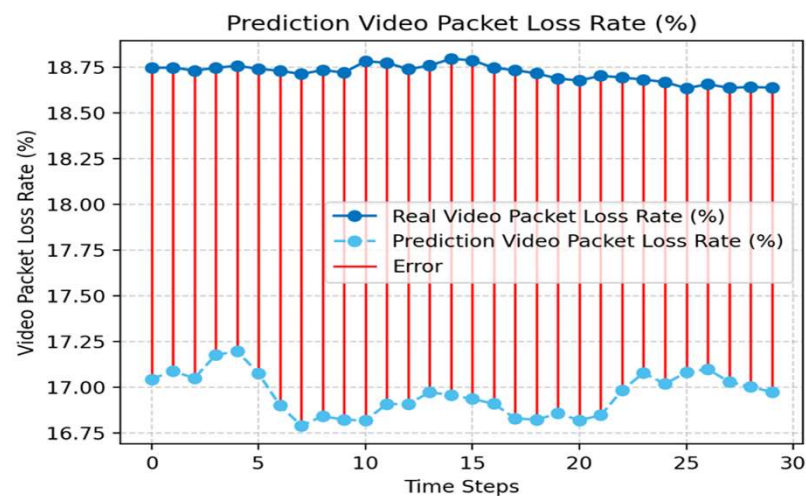
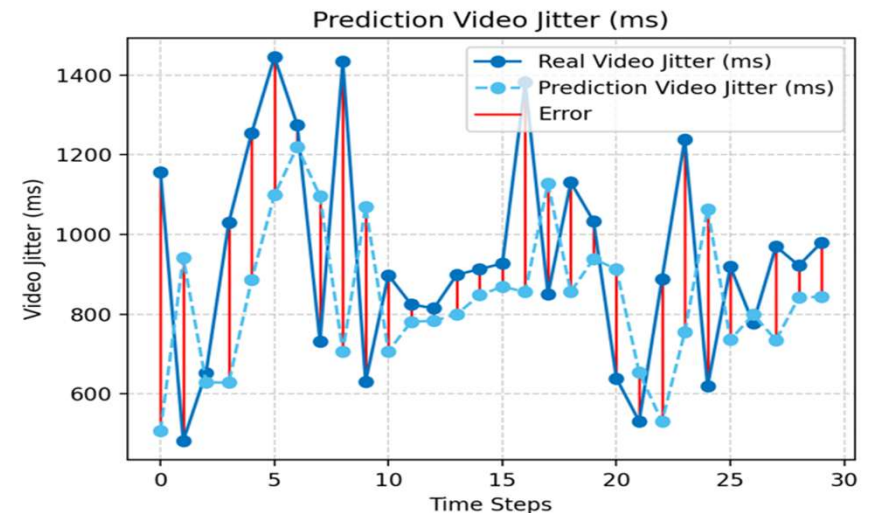
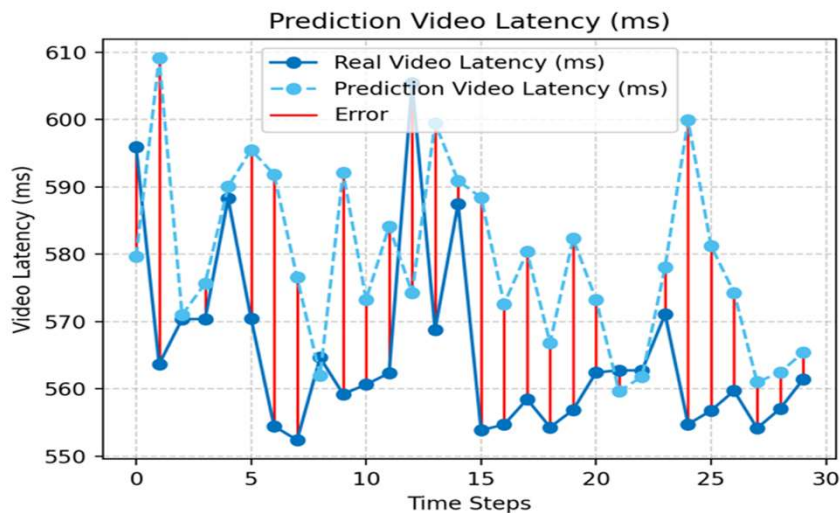
Results and analysis

Scenario 3 - Critical Quality (Audio)



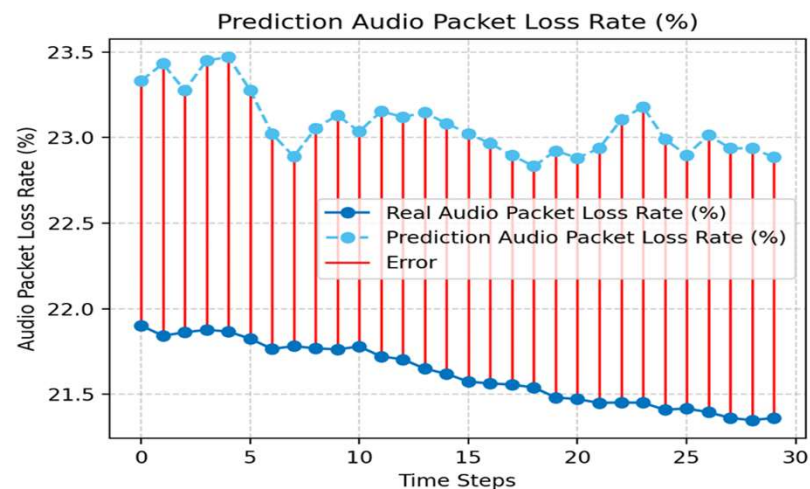
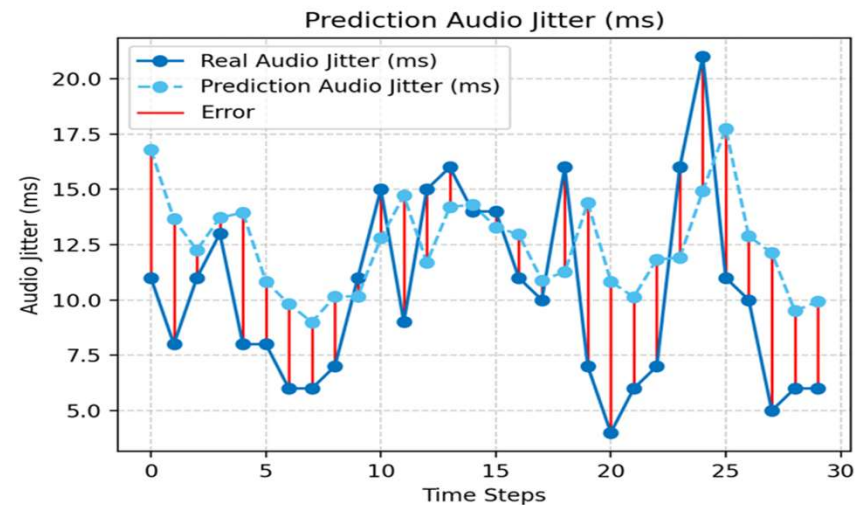
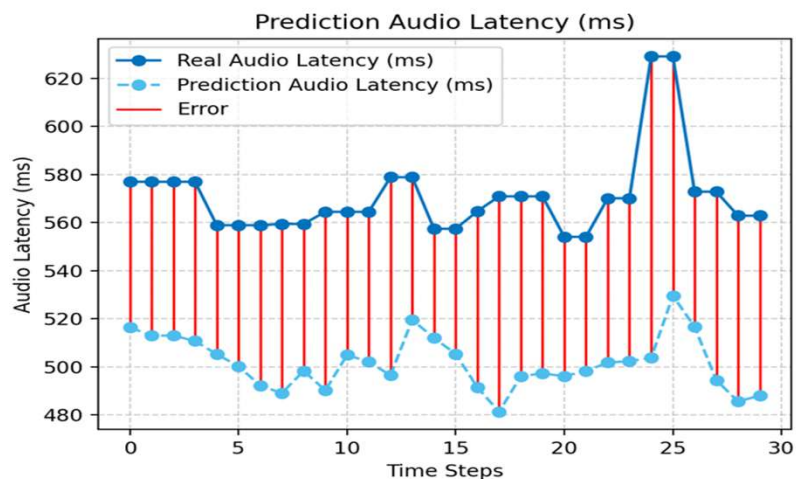
Results and analysis

Scenario 4 - Extreme Condition (Video)



Results and analysis

Scenario 4 - Extreme Condition (Audio)



送別

-
- The slide displays a presentation titled "Development of a WebRTC-based Calling Application to Predict Quality of Service Patterns Using an Artificial Neural Network". The presenter, a woman in a grey blazer, is standing next to a large screen. The screen shows a video call with two participants and a complex flowchart. The flowchart, written in red and blue ink, illustrates the system's architecture. It starts with "Quality Care" leading to "Activated", which then branches into "Dobvlet Menet" and "Predict". "Predict" leads to "Quality", which then leads to "Pretters" and "Of Service". "Of Service" leads to "Devitecyl Potmbes". The flowchart also includes "Pident" and "Recoll" which lead to "Widites". The video inset shows two people in a call, with a "Ton" and "Sincb" box below them.
- ```

graph TD
 QC[Quality Care] --> Activated
 Activated --> DobvletMenet[Dobvlet Menet]
 Activated --> Predict
 Predict --> Quality
 Quality --> Pretters
 Quality --> OfService[Of Service]
 OfService --> DevitecylPotmbes[Devitecyl Potmbes]
 Pident --> Recoll
 Recoll --> Widites

```
- The video inset shows two people in a call, with a "Ton" and "Sincb" box below them.

# Conclusion

- ❑ The integration of technologies such as WebRTC and RNNs represents a viable and modern alternative for addressing the problem of QoS prediction in video-call applications.
- ❑ WebRTC, as a base technology, facilitates the creation of real-time communication environments with measurement and adaptation capabilities, removing previous technological barriers.
- ❑ LSTM-type neural networks are capable of capturing the temporal behavior of the evaluated metrics (latency, jitter, and packet loss rate), allowing the anticipation of their future evolution with an acceptable level of accuracy, especially under stable or moderately degraded conditions.



# Conclusion

- ❑ One of the most significant contributions of this work was demonstrating that a deep-learning-based model can be fed with the first few minutes of a call to generate reliable predictions of its future behavior.
- ❑ The adopted predictive approach demonstrated robustness when trained across multiple network scenarios, which allowed the neural network to learn diverse patterns and therefore generalize better under new conditions.



# Future Work

- ❑ **The following recommendations are proposed to strengthen the developed solution and encourage future research:**
  - **Expansion of the dataset.**
  - **Inclusion of new QoS and QoE metrics.**
  - **Implementation of the model in real production environments.**
  - **Exploration of more complex architectures.**
  - **Design of autonomous network management systems.**



# Questions

**“The important thing is not to stop questioning.”**

**Albert Einstein**



**next** EDUCACIÓN

**C**  
Fundación  
Carolina

PhD. Carlos Moreno.

Universidad Central de Venezuela.

Universidad de La Rioja

OBS Business School

**carlosmanuel.moreno.ucv@gmail.com**

**+58-414-9191033**



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