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Enhancing Spectrum Sensing For 5G and LTE With Improved U-Net Architecture

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Major: Computer Engineering Technology
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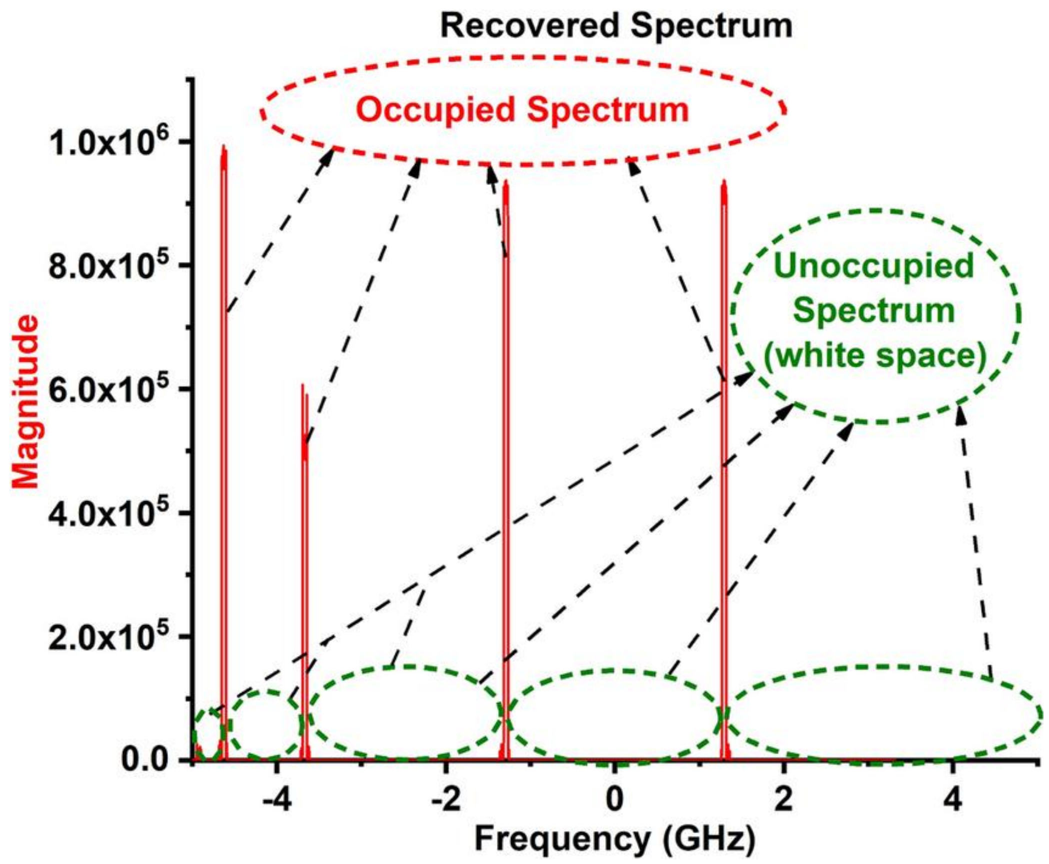
Fields of research: Signal processing, Deep learning

1. Introduction
2. Contribution
3. Methology
4. Proposal model
5. Evaluation result
6. Conclusion

Spectrum sensing definition & Challenges

- **Definition of Spectrum Sensing:** Identifying the availability and non availability of wireless or radio communication networks in particular frequency bands.
- **Problem with Traditional Frequency Allocation:** Traditional frequency allocation schemes may fail to meet high data rate demands, leading to inefficient use of spectrum resources.
- **Spectrum Resource Utilization:** Unused spectrum resources can be allocated to other communication systems in need, like 5G NR (New Radio) and LTE (Long-Term Evolution).
- **Importance for 5G NR and LTE:** Spectrum sensing has become a key topic for 5G NR and LTE, with a focus on managing and optimizing the use of limited spectrum resources.
- **Challenges and Focus Areas:** The main challenge is enhancing the performance of monitoring and managing limited spectrum resources more effectively.



[1] T. Huynh-The, Q.-V. Pham, T.-V. Nguyen, T. T. Nguyen, R. Ruby, M. Zeng, and D.-S. Kim, "Automatic modulation classification: A deep architecture survey," *IEEE Access*, vol. 9, pp. 142 950–142 971, Oct. 2021.
[3] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," IEEE Communications Surveys & Tutorials, vol. 11, no. 1, pp. 116–130, Mar. 2009.

Spectrum sensing based on Deep Learning

- **Existing Sensing Techniques:** Various techniques such as sensing algorithms, multi-dimensional spectrum sensing, channel estimation, and cooperative sensing have been introduced for spectrum sensing.
- **Hardware Challenges:** Spectrum sensing faces significant hardware challenges, requiring high sampling rates, high-resolution analog-to-digital converters (ADCs) with large dynamic ranges, and high-performance processors.
- **Cognitive Wireless Communication:** Cognitive wireless communication systems are categorized based on sensing duration and frequency.
- **Trade-off Between Performance and Complexity:** Spectrum sensing methods involve balancing performance with the complexity of sensing algorithms.
- **Research Focus:** Researchers have been working on improving spectrum sensing to address challenges and develop innovative solutions that enhance accuracy and performance in cognitive wireless networks.
- **Machine Learning-Based Solutions:** Recent research includes the use of machine learning to create intelligent spectrum sensing solutions, which are comprehensively reviewed in several prominent surveys.

[3] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," IEEE Communications Surveys & Tutorials, vol. 11, no. 1, pp. 116–130, Mar. 2009.
[4] A. Kumar, N. Gaur, S. Chakravarty, M. H. Alsharif, P. Uthansakul, and M. Uthansakul, "Analysis of spectrum sensing using deep learning algorithms: CNNs and RNNs," Ain Shams Engineering Journal, vol. 15, no. 3, p. 102505, Mar. 2024.
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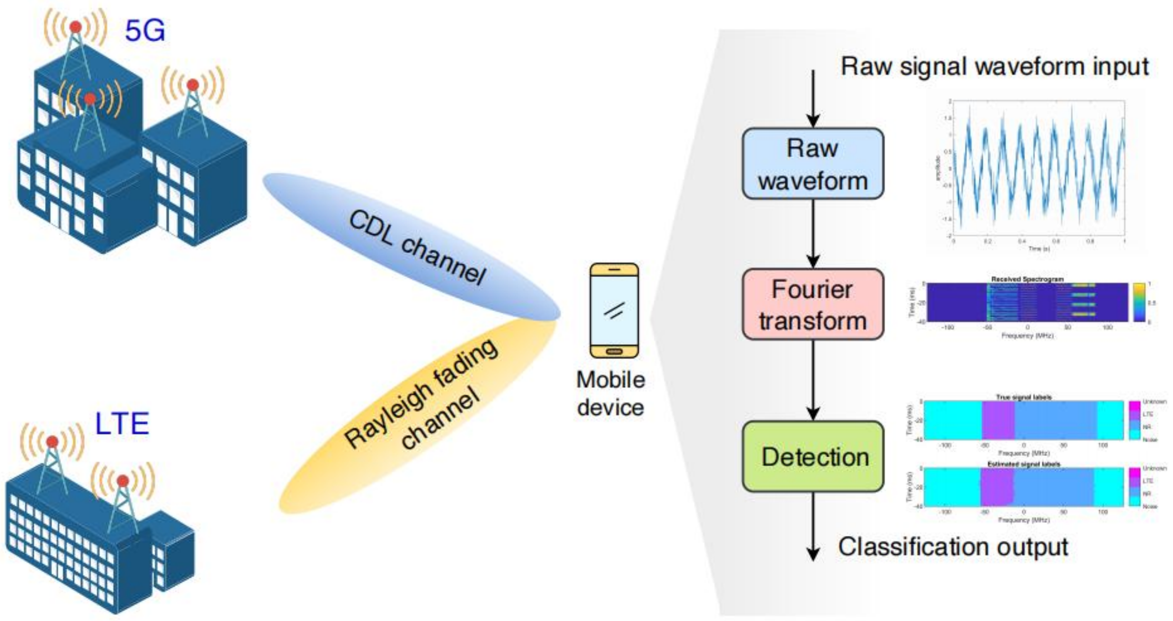
Spectrum sensing based on Deep Learning infastructure

Spectrum sensing based on deep learning uses deep learning model to dectect spectrogram and predict signal lables in specific bandwith. Therefore, it provide higher prediction performance than other methods



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[9] G.-V. Nguyen, C. V. Phan, and T. Huynh-The, "Accurate spectrum sens_x0002_ing with improved DeepLabV3+ for 5G-LTE signals identification," in Proc. 12th International Symposium on Information and CommunicationTechnology (SOICT), Ho Ch iMinh, Vietnam, Dec. 2023, pp. 221–227.

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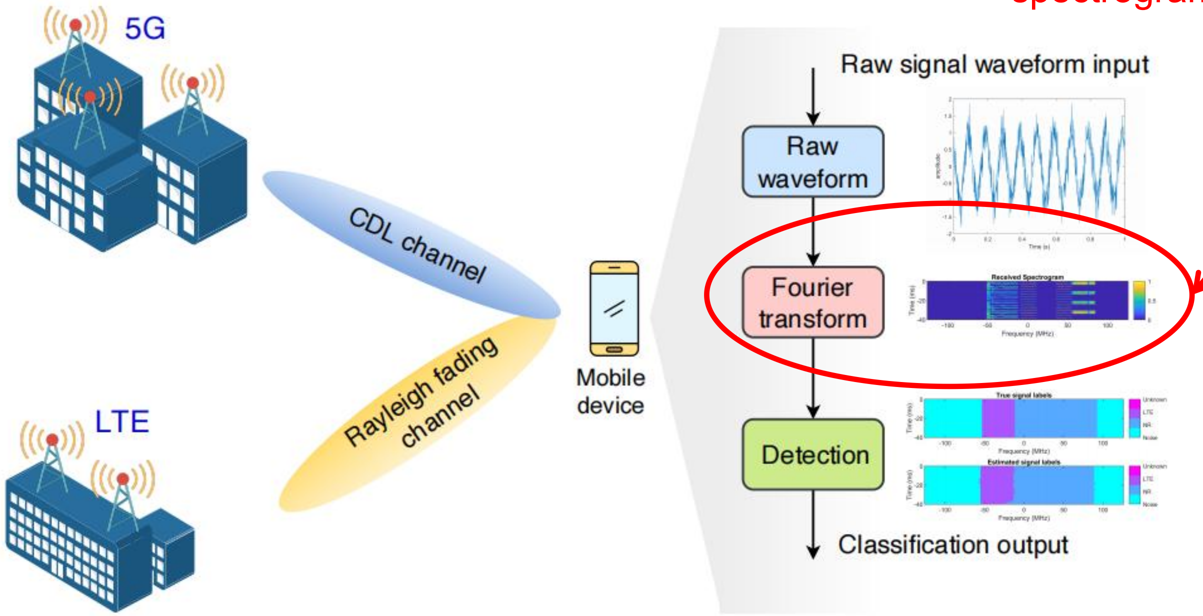
Raw communication signals will be transfered to spectrogram (2D) by fast fourier transform



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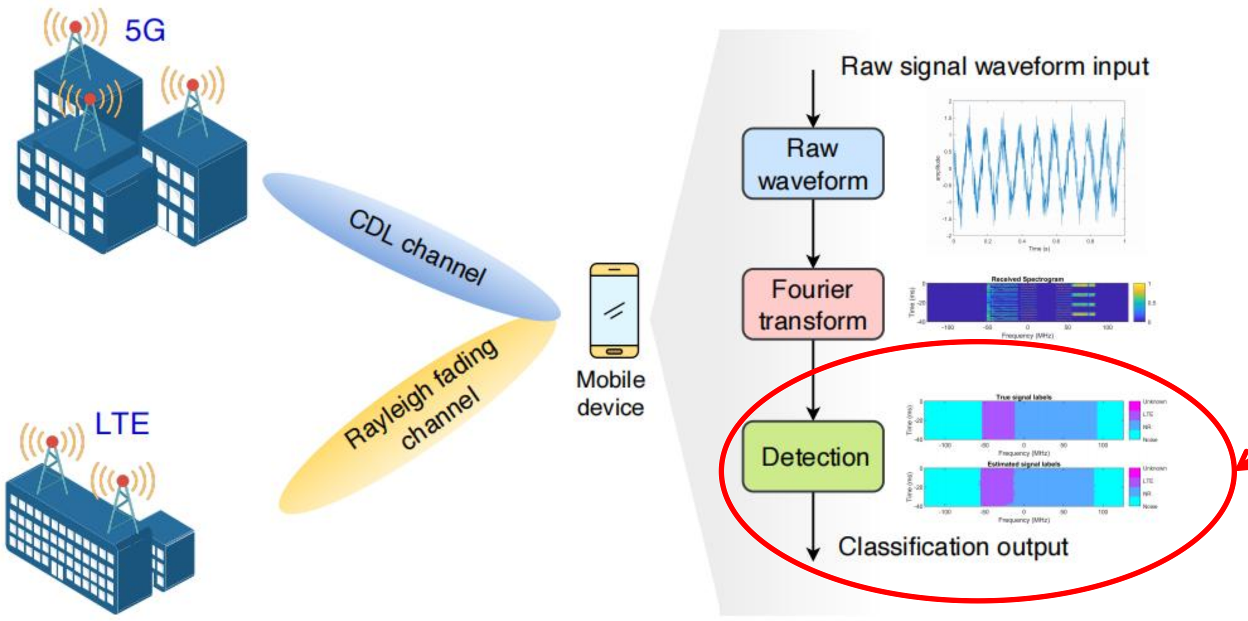

Applying Deep learning model to predict signal lables in specific bandwith at this process

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- **Proposal of SpecSenseNet:** A new U-Net-based deep network architecture called Spectrum Sensing Network (SpecSenseNet) is proposed, designed to reduce network size and enhance performance for 5G and LTE signals.

- **SpecSenseNet Enhancements:** SpecSenseNet addresses these limitations by incorporating:
  - **Depth-wise separable convolutions:** Reduce computational complexity in both encoder and decoder paths.
  - **Recurrent residual convolutions:** Replace standard U-Net blocks to maintain segmentation accuracy.
  - **Atrous Pyramid Spatial Pooling:** Injected between the encoder and decoder to enhance feature learning at multiple scales.

- **Contributions:**
  - Reduction of network's parameters.
  - Maintenance of segmentation accuracy.
  - Inclusion of efficient modules like depth-wise convolutions and Atrous Pyramid Spatial Pooling.

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[13] F. Chollet, "Xception: Deep learning with depthwise separable convo_x0002_lutions," in Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, Nov. 2017, pp. 1800–1807.
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[17] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, "DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 40, no. 4, pp. 834–848, Apr. 2018.

Signal model

RX signal in time domain

$$y(t) = x(t) * h(t) + n(t)$$

- y(t): the RX signal
- x(t): the transmitted signal (TX signal)
- h(t): the channel response
- n(t): additive white Gaussian noise (AWGN)

signal transformation in frequency domain using Short-time Fourier transform (STFT)

$$Y(\tau, w) = \int_{-\infty}^{\infty} y(t) \cdot w(t - \tau) \cdot e^{-j2\pi ft}\, dt$$

- Y (τ, w): the spectrogram of the RX signal
- y(t): the input RX signal
- w(t − τ): window function

Energy of signal

$$E = \sum_{f=f_{min}}^{f_{max}} |Y(\tau, w)|^2$$

- E: the energy density in the range of frequency
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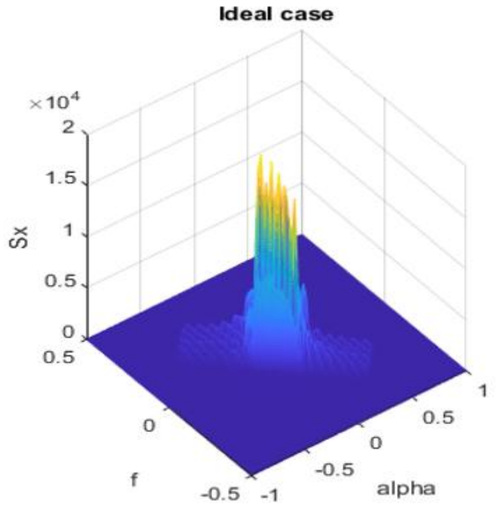
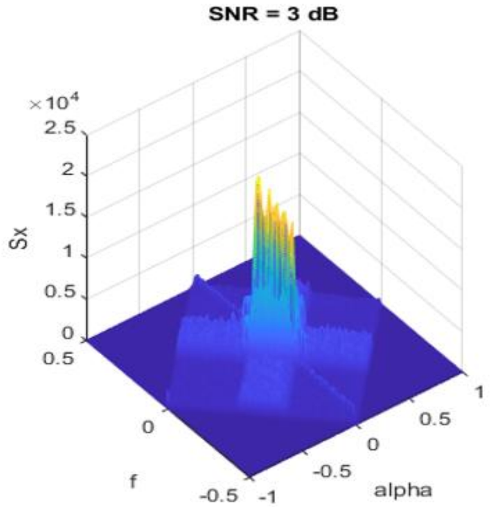
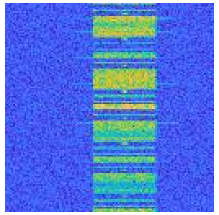
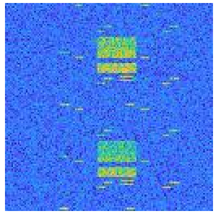




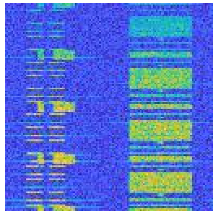
Spectrogram sample



LTE



5G NR



LTE & 5G

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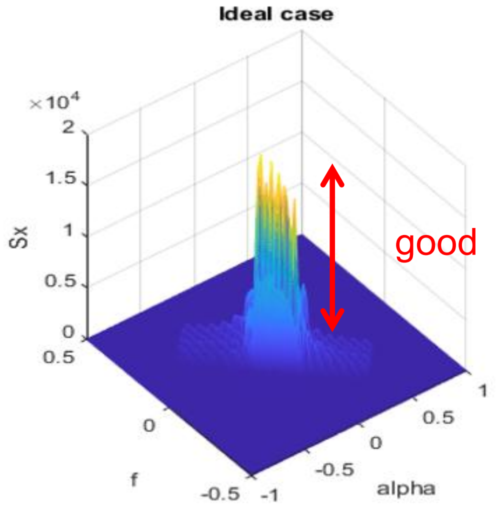

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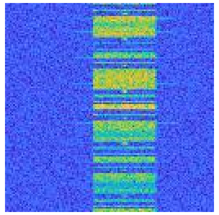

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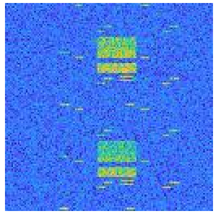

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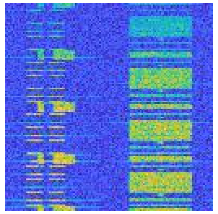
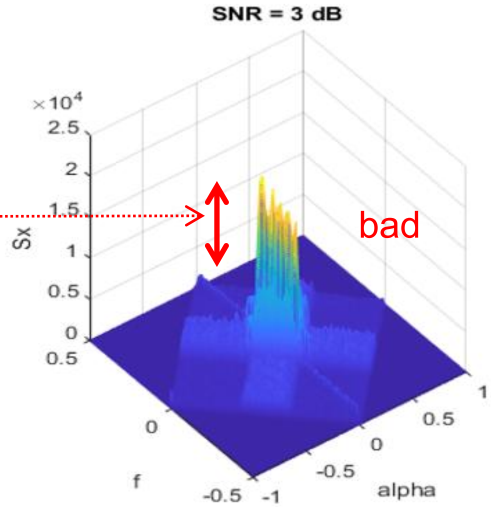


LTE & 5G

The gap energy between real signal and noise called **SNR** (dB)



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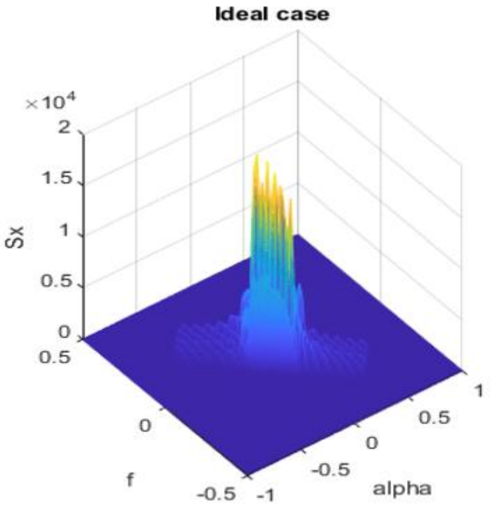

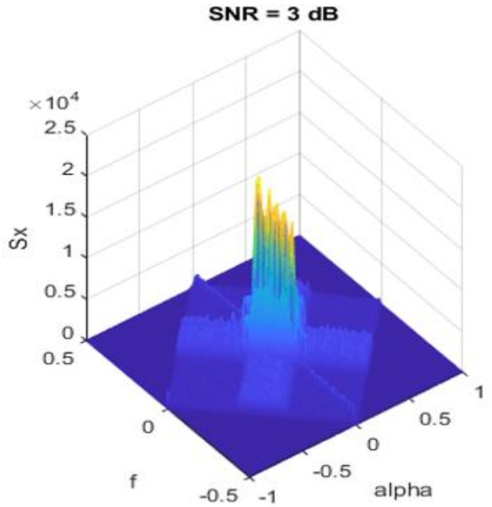

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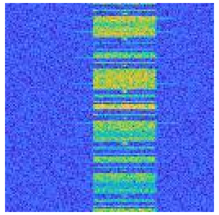
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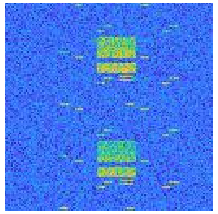
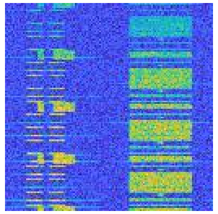

5G NR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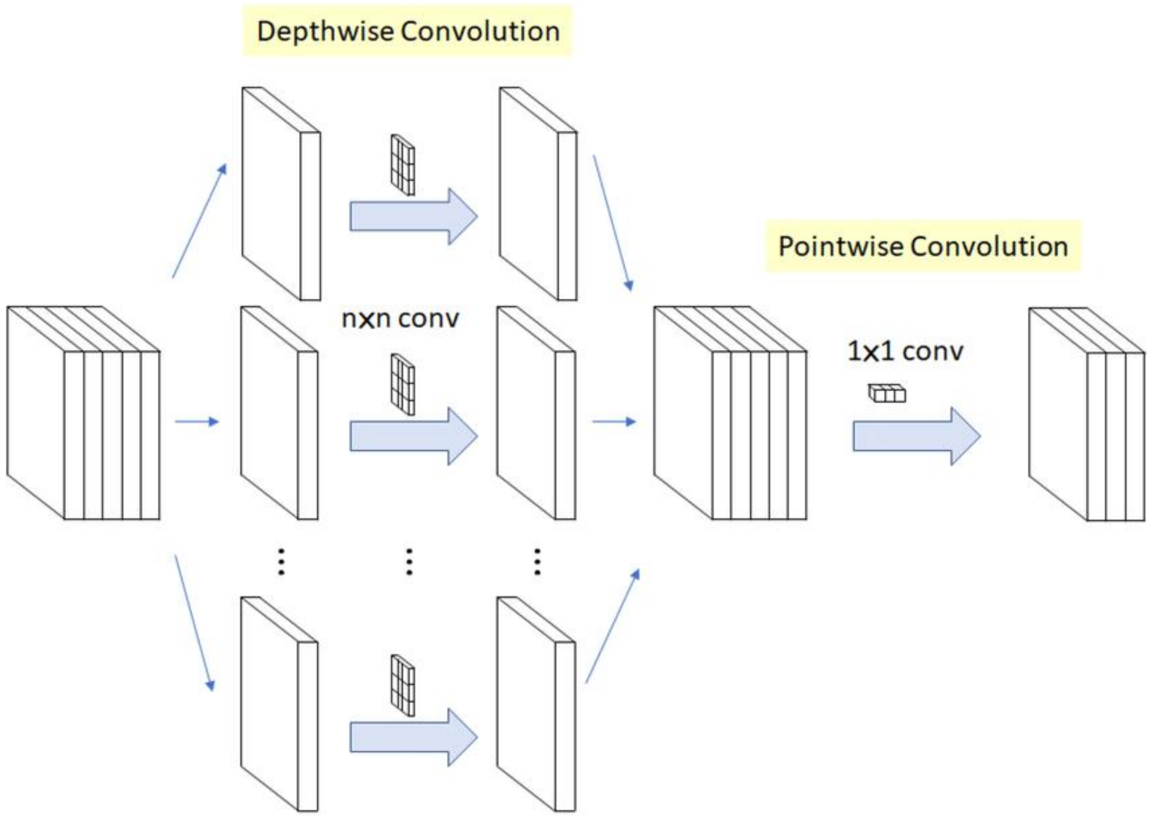

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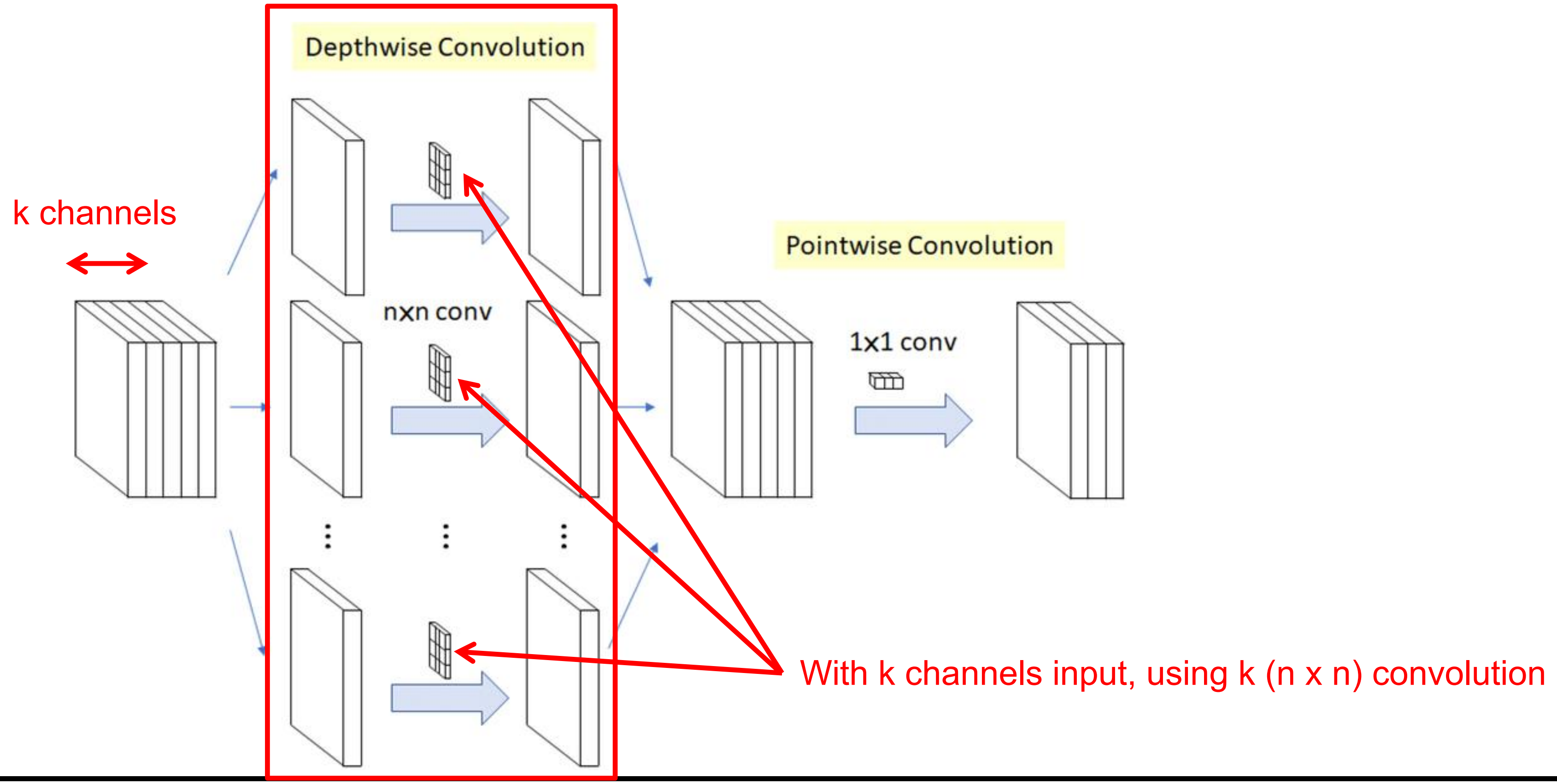

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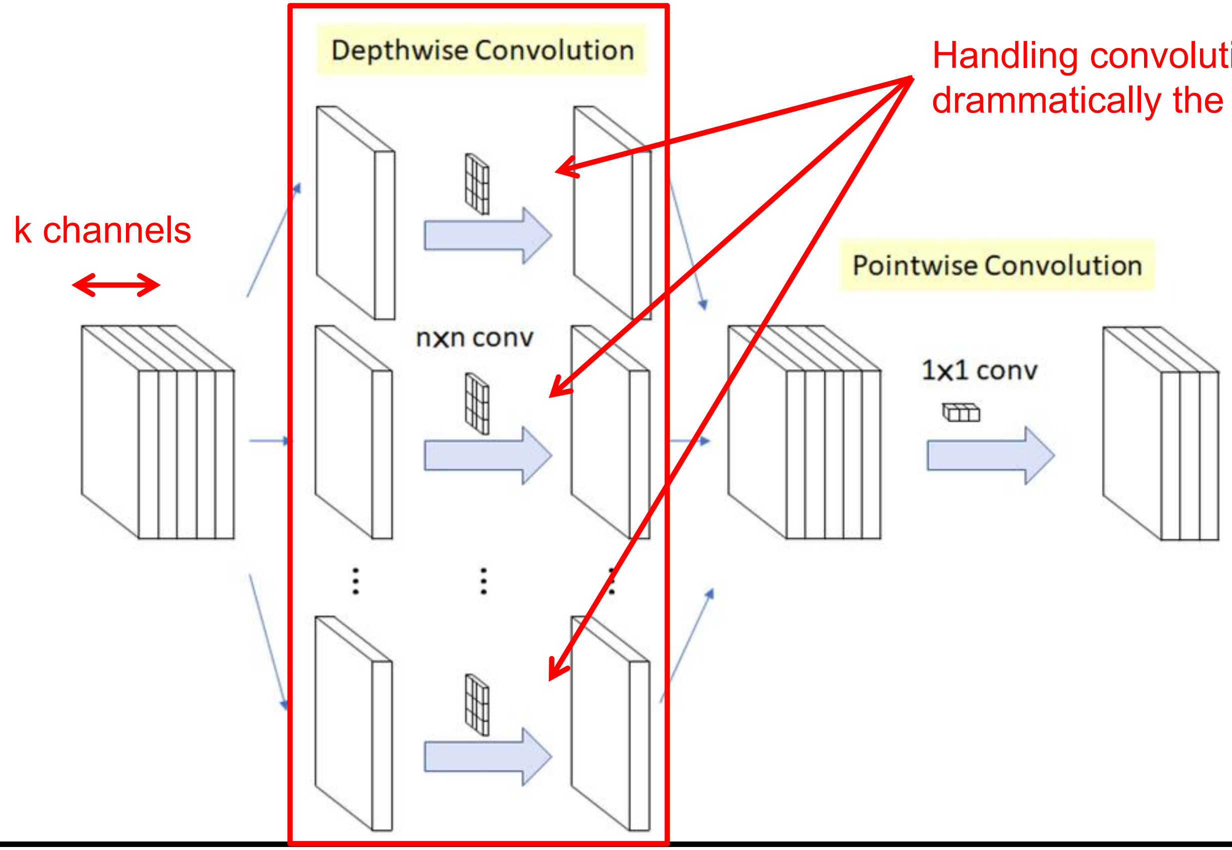
Handling convolution with 2 dimension reduces drammatically the trainable parameters



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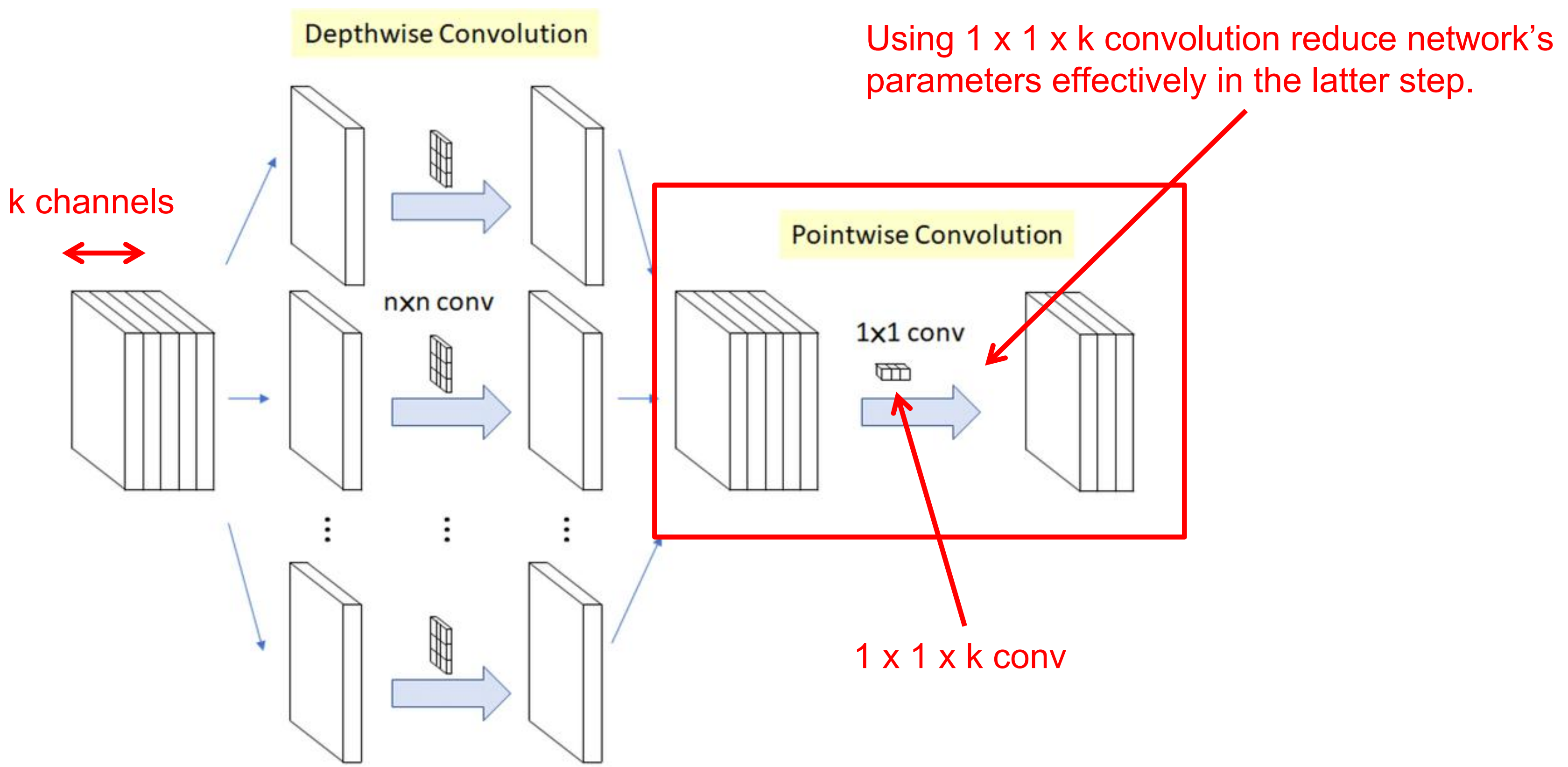

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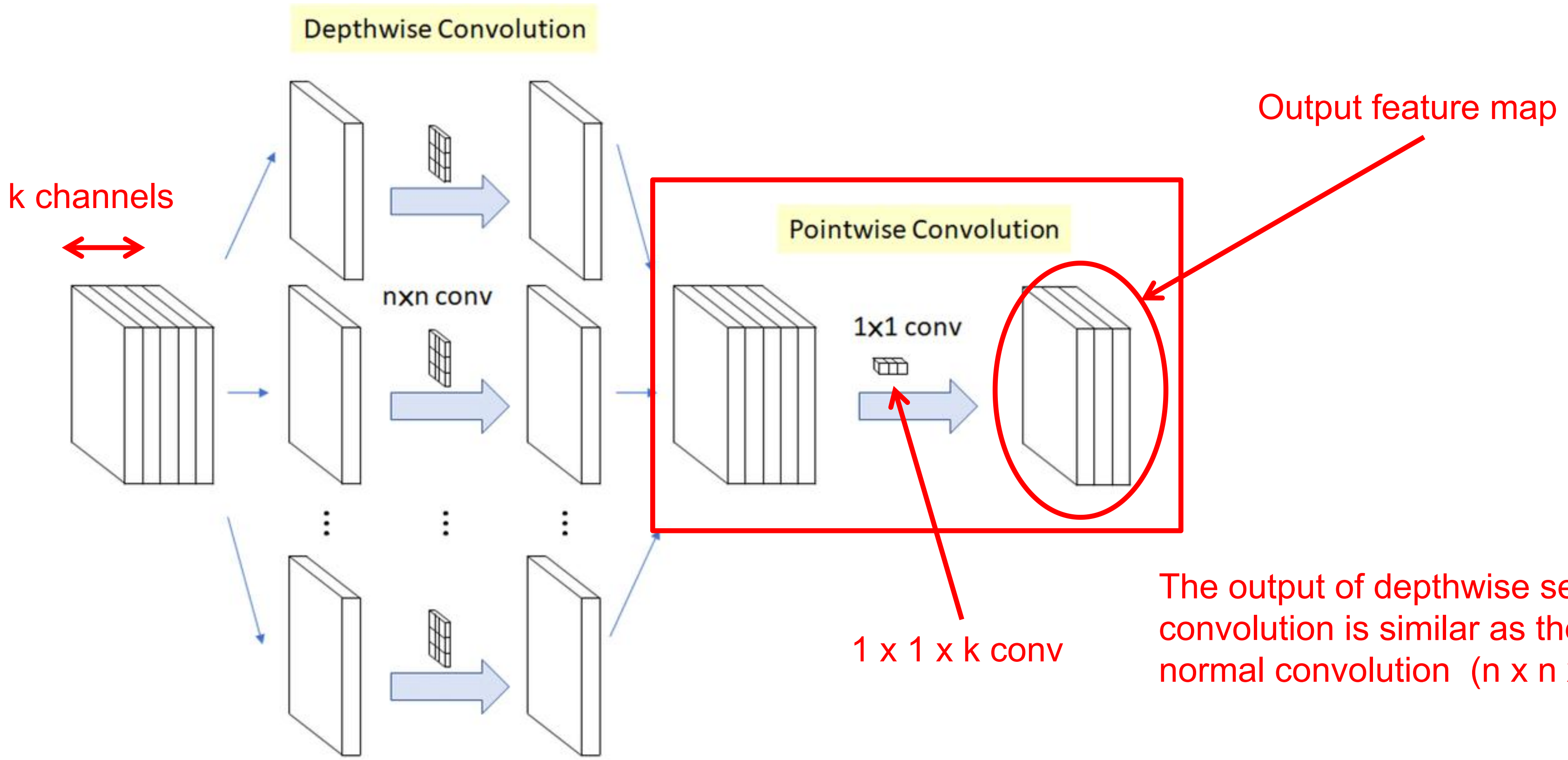

The output of depthwise separable convolution is similar as the output of normal convolution (n x n x k)

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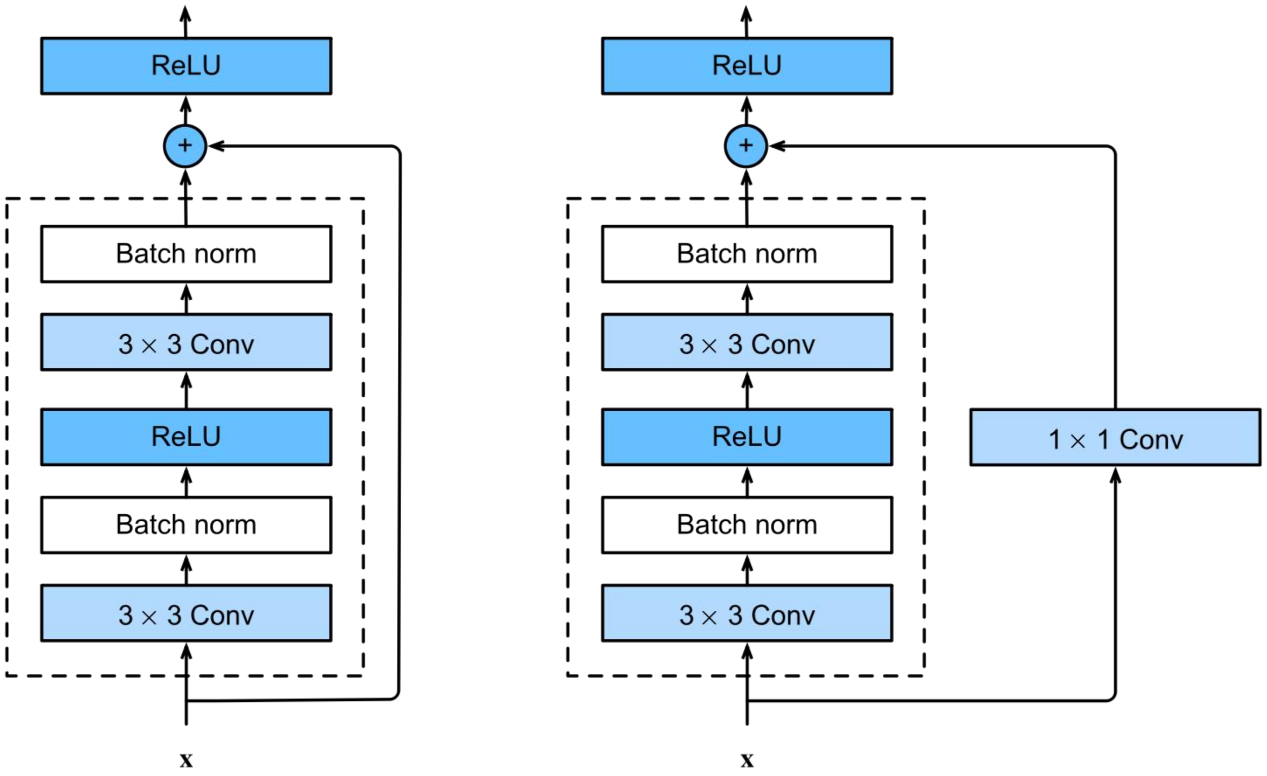
Recurrent residual convolution

Recurrent residual convolution contains residual connection helping the network skip unessential convolution block, which is determined by input data.



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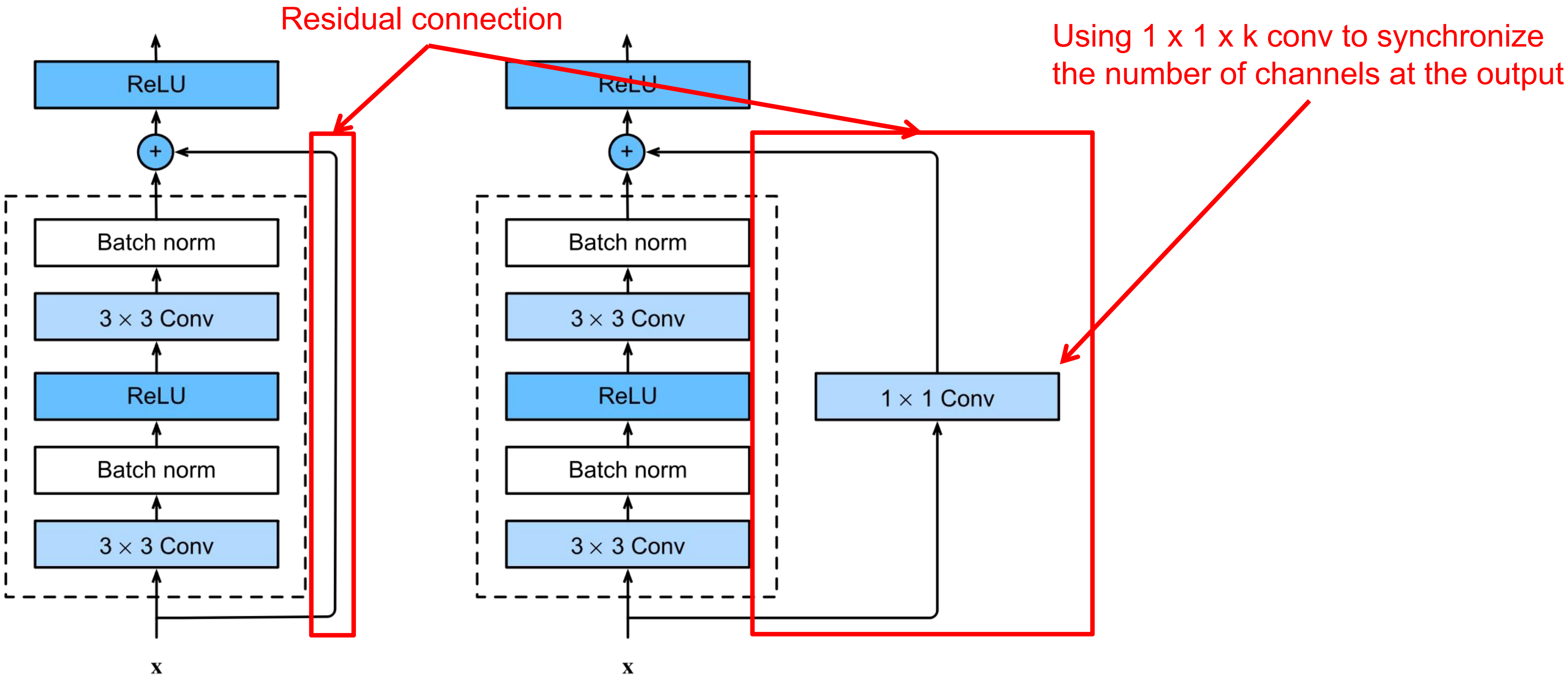

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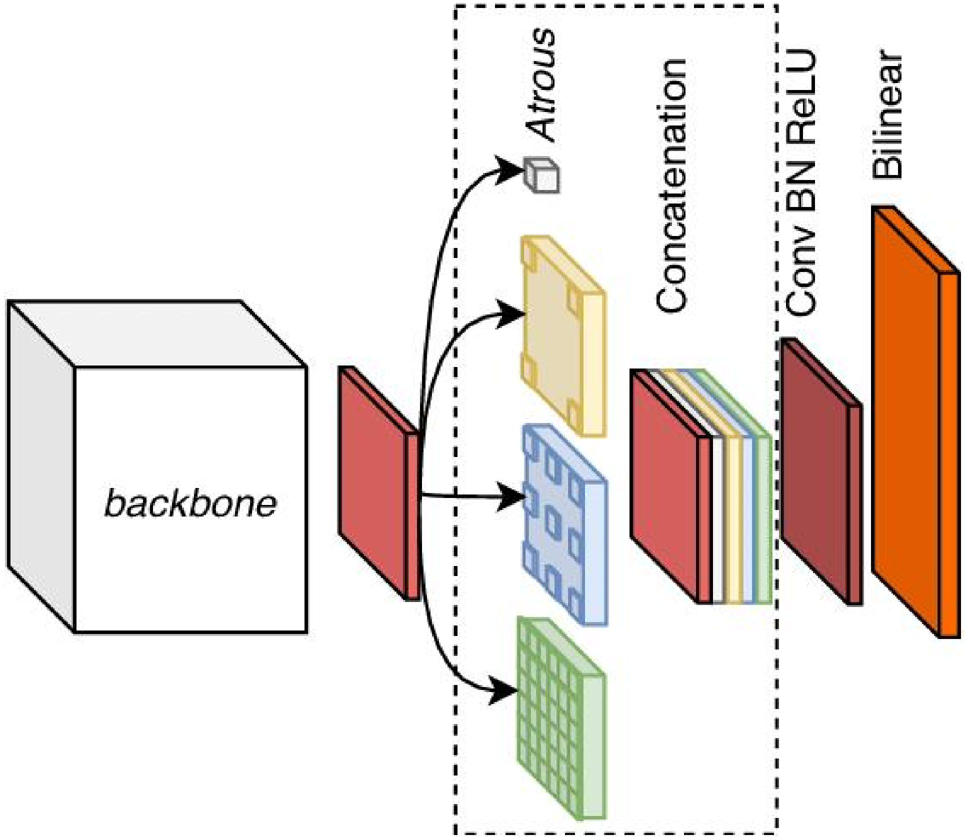
Atrous Pyramid Spatial Pooling

Atrous pyramid spatial pooling implements paralell convolution with different multiple sampling rates. It help network retain many general feature maps of the output

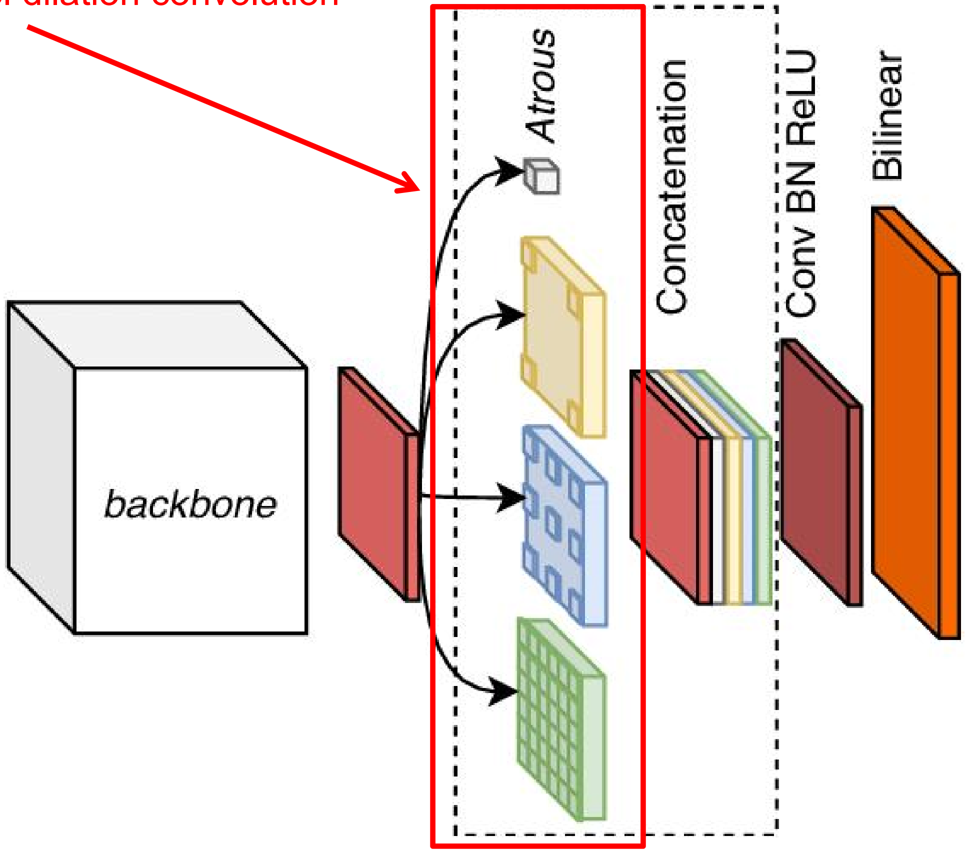


[17] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, "DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 40, no. 4, pp. 834–848, Apr. 2018.

Atrous Pyramid Spatial Pooling

Atrous pyramid spatial pooling implements paralell convolution with different multiple sampling rates. It help network retain many general feature maps of the output

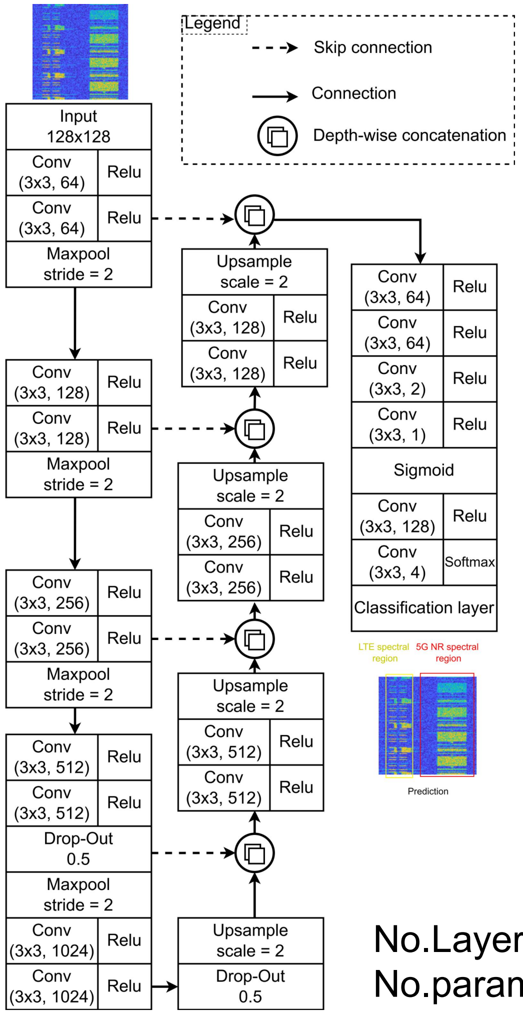
Dilate convolution with different rates, it extracts feature maps with many parallel dilation convolution



[17] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, "DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 40, no. 4, pp. 834–848, Apr. 2018.

We apply above deep learning techniques to improve Unet architecture

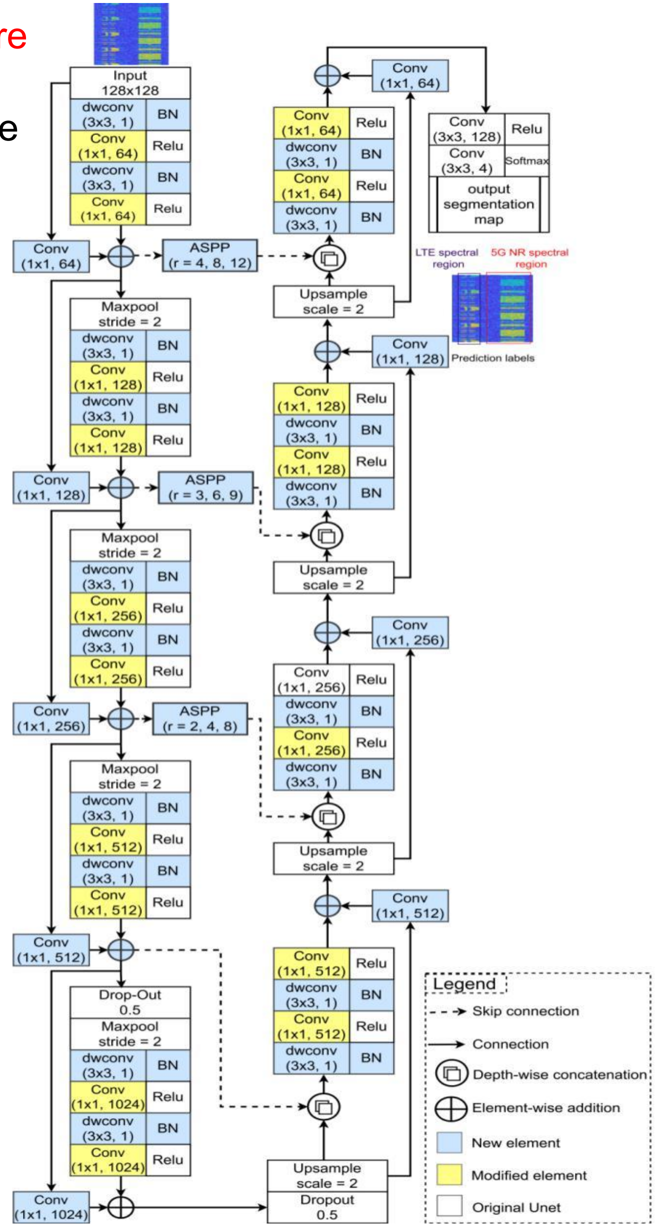
U-Net architecture



No.Layers: 59
No.params: 31.3M

Improvement

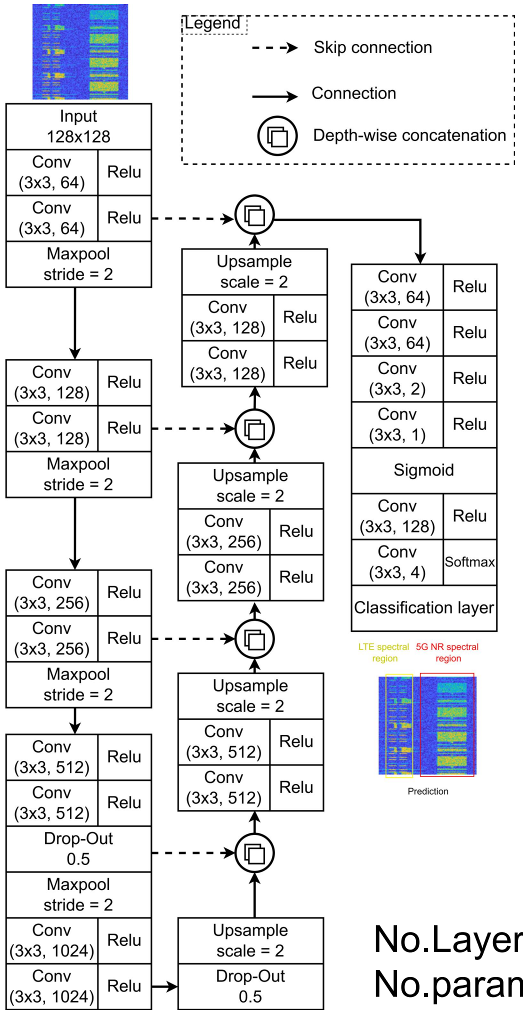
SpecSenseNet architecture



No.Layers: 125
No.params: 7.8M

We apply above deep learning techniques to improve Unet architecture

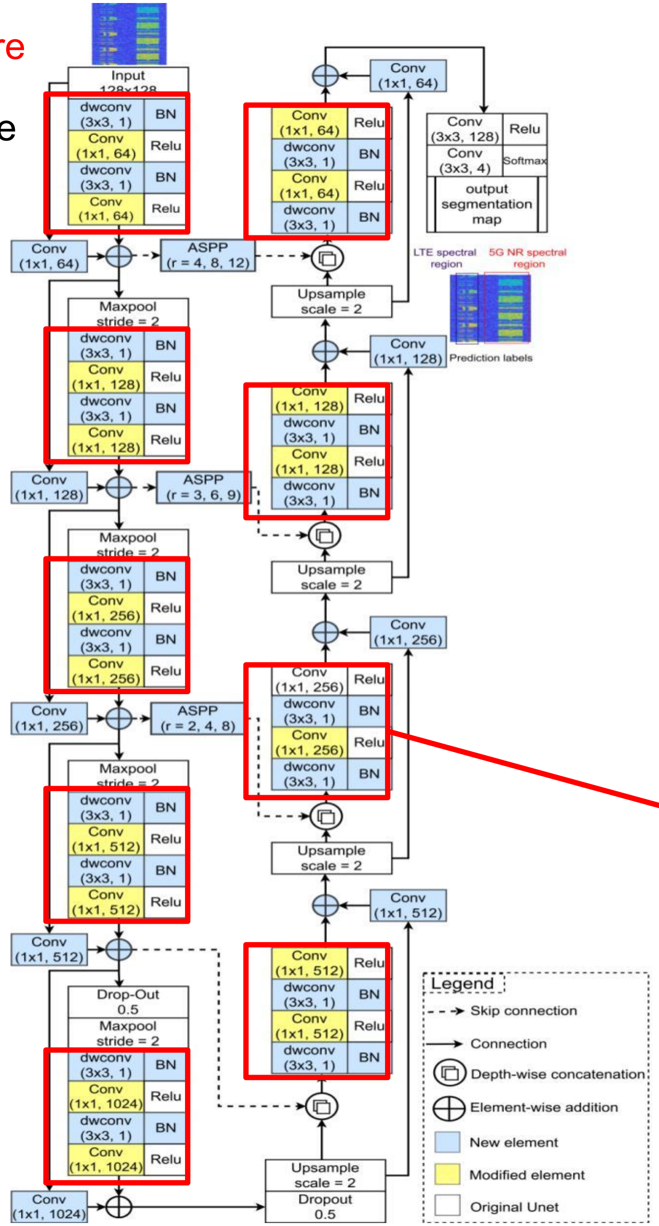
U-Net architecture



No.Layers: 59
No.params: 31.3M

SpecSenseNet architecture

Improvement



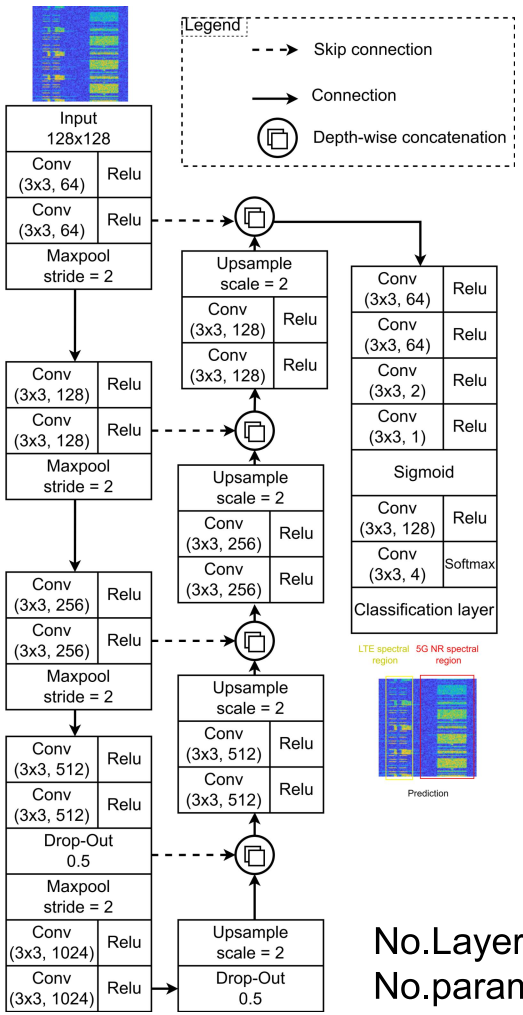
All convolutions are replace by depth-wise sparable convolution. It contributes to reudce drammatically the number of paramers in our network

$$F_{out}^{DSC} = relu(pconv(bn(dwconv(F_{in}^{DSC}))))$$

No.Layers: 125
No.params: 7.8M

We apply above deep learning techniques to improve Unet architecture

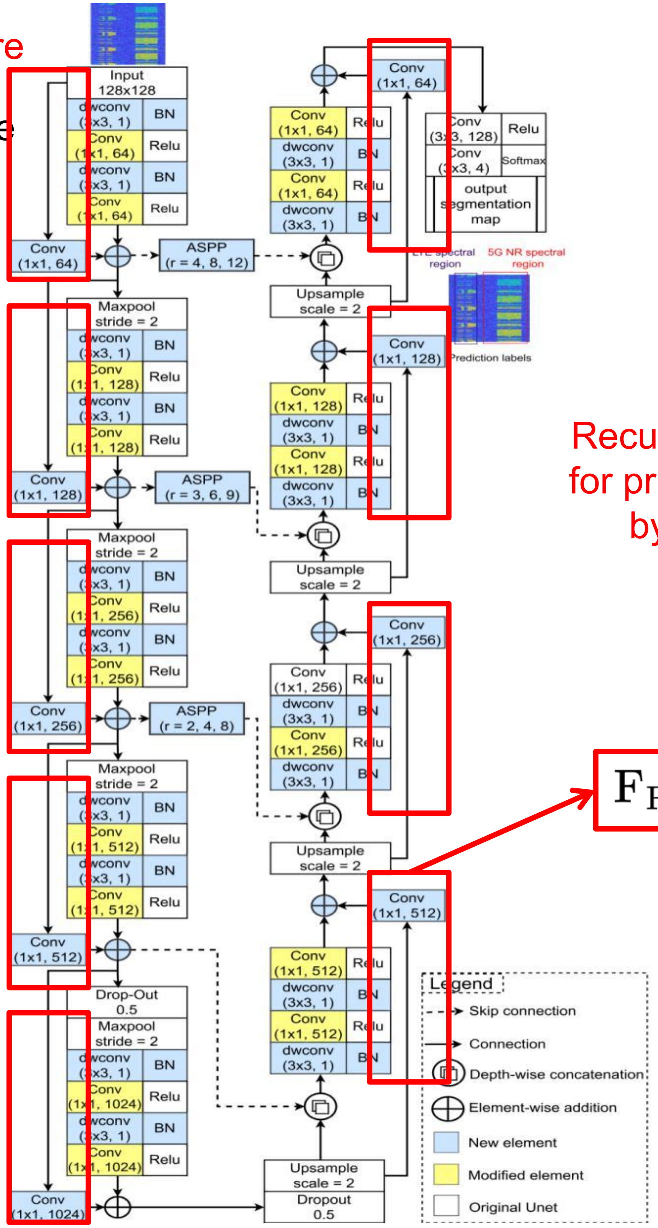
U-Net architecture



No.Layers: 59
No.params: 31.3M

SpecSenseNet architecture

Improvement



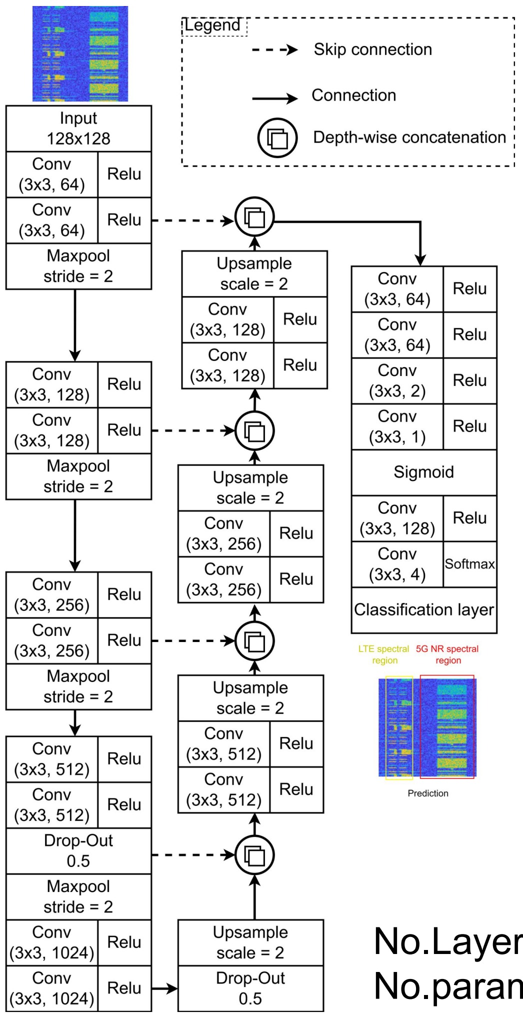
Recurrent residual convolution are used for pruning our network that determinate by dataset. It contribute to ignore unimportant features

$$\mathrm{F}_{\mathrm{RRB}} = \mathrm{F}_{\mathrm{out}}^{\mathrm{DSC}} + \mathrm{conv}(1 \times 1, \mathrm{F}_{\mathrm{in}}^{\mathrm{DSC}})$$

No.Layers: 125
No.params: 7.8M

We apply above deep learning techniques to improve Unet architecture

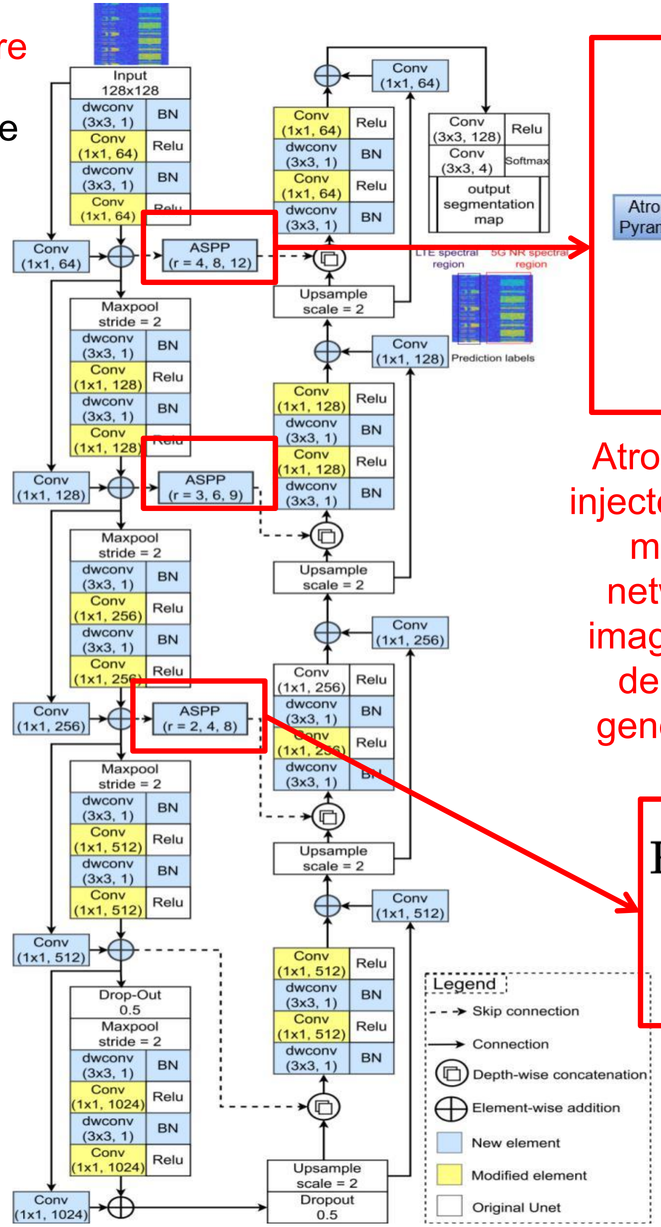
U-Net architecture

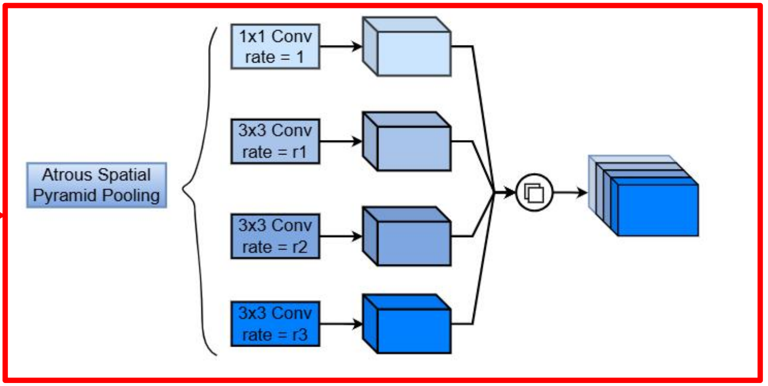


No.Layers: 59
No.params: 31.3M

SpecSenseNet architecture

Improvement





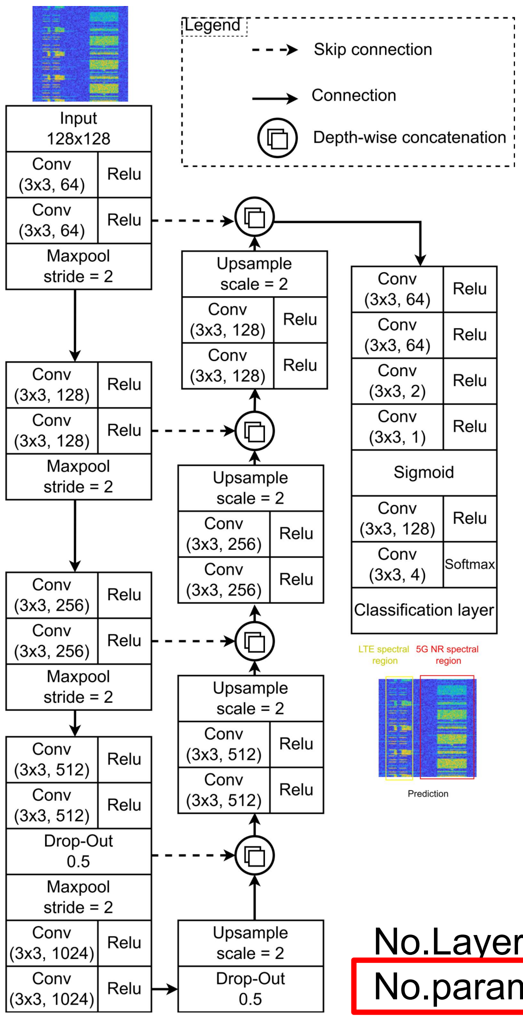
Atrous spatial pyramid pooling modules are injected into skip connection wires to feature in multiple receptive feild sizes. It help our network retain general information of input image during encoder process and pass it to decoder process directly. As a result, the general importance information is remained correctly

$$
\mathrm{F}_{\mathrm{out}}^{\mathrm{ASPP}} = \mathrm{concat}(\mathrm{conv}(1 \times 1, \mathrm{F}_{\mathrm{in}}^{\mathrm{ASPP}}), \mathrm{conv}(3 \times 3, \mathrm{F}_{\mathrm{out}}^{\mathrm{ASPP}}, \mathrm{r}_1), \mathrm{conv}(3 \times 3, \mathrm{F}_{\mathrm{out}}^{\mathrm{ASPP}}, \mathrm{r}_3))
$$

No.Layers: 125
No.params: 7.8M

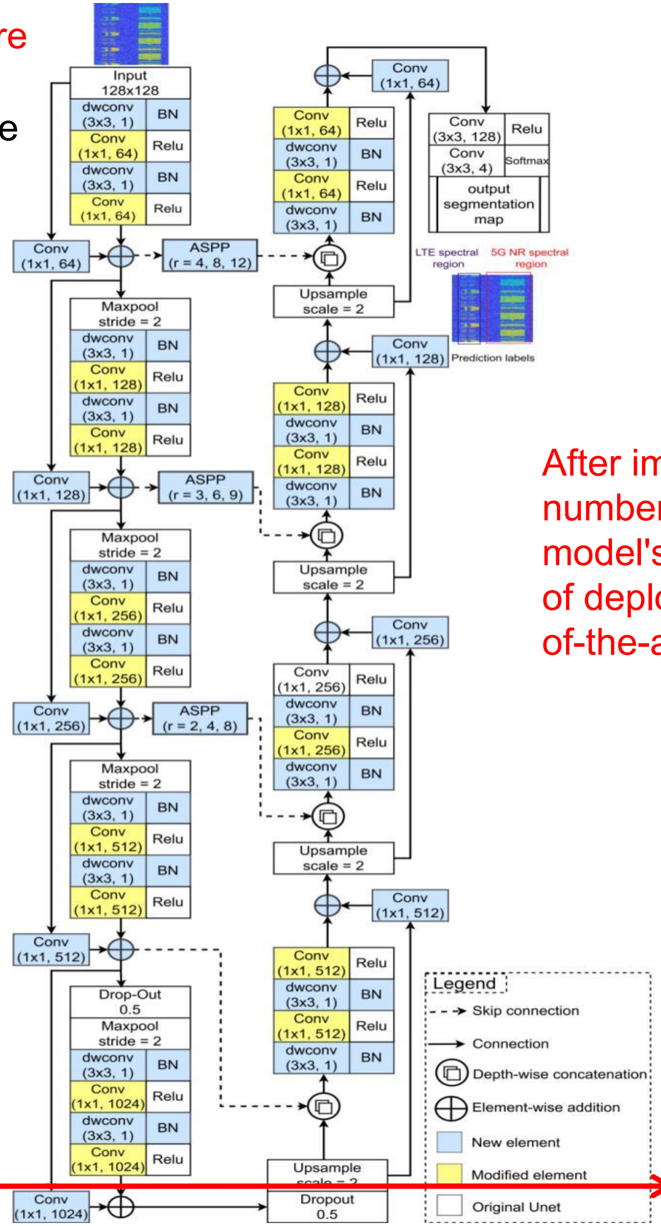
We apply above deep learning techniques to improve Unet architecture

U-Net architecture



SpecSenseNet architecture

Improvement



After improvement, we successfully reduce the number of parameter for SpecSenseNet. the model's efficiency, generalizability, and ease of deployment are enhanced, leveraging state-of-the-art approaches

Reducing by 23.5M

No.Layers: 59
No.params: 31.3M

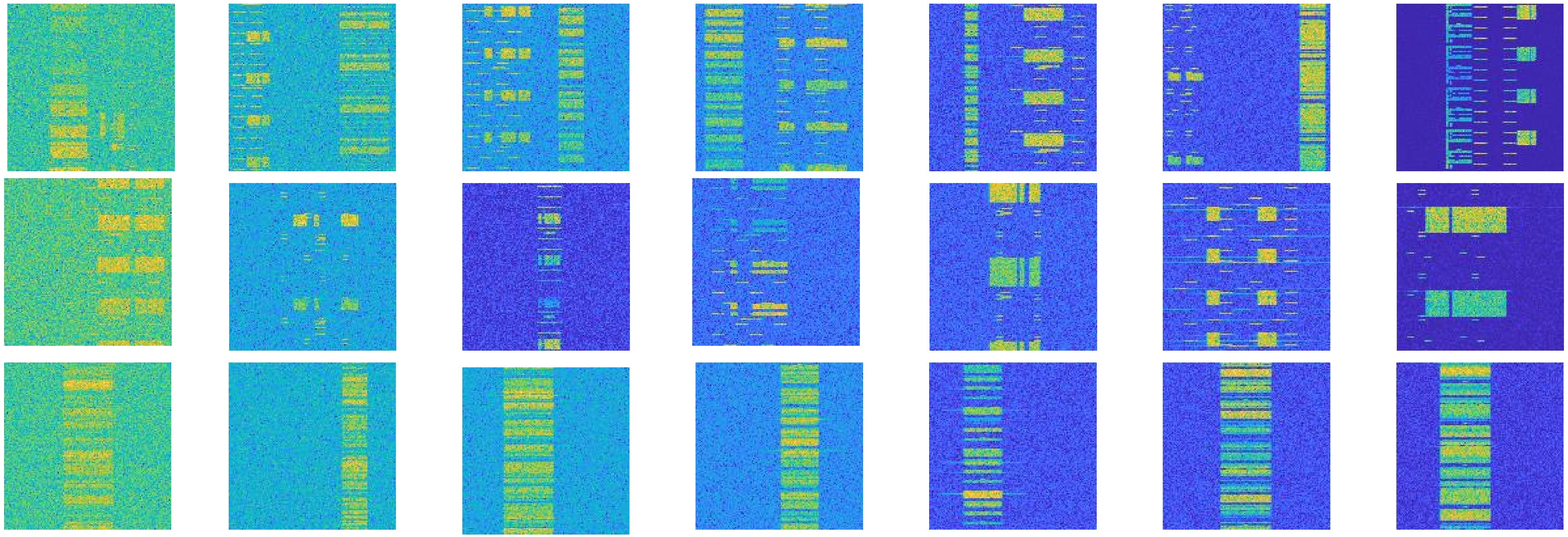
No.Layers: 125
No.params: 7.8M

Dataset Information

Overlapping 5G & LTE spectrogram datasets

5G spectrogram datasets

LTE spectrogram datasets



0 dB | 5 dB | 10 dB | 15 dB | 20 dB | 25 dB | 30 dB

Dataset information

Catelogy	No.Samples	Image size	SNR (dB)
LTE	5,000	128x128	[0 30]
5G	5,000	128x128	[0 30]
5G & LTE	5,000	128x128	[0 30]

Hardware resource & Training options

MATLAB

Hardware resource	
CPU	3.0 GHz
GPU	RTX 2080
Memory	16 GB
MatLab version	R2023

Training options	
No.epoch	40
Learning rate	0.001
Learning rate schedule	piecewise
Validation frequency	1000

Dataset Information

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5G	5,000	128x128	[0 30]
5G & LTE	5,000	128x128	[0 30]

In term of evaluation, we use Matlab to train and evaluate the deep learning networks. On the other hand, the datasets are generated from 5G & LTE tool box, which help our simulate real 5G & LTE signals under various noise density (difference SNR)

Hardware resource & Training options

MATLAB

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GPU	RTX 2080
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5G & LTE	5,000	128x128	[0 30]

We divide dataset into 80% for training, 10% for validation, and 10% for testing from 1,500 images ramdomly.

Hardware resource & Training options

MATLAB

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The image sizes are reduce to 128x128 that requires lower memory resource.

Hardware resource & Training options

Hardware resource	
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5G & LTE	5,000	128x128	[0 30]

We train the spectrogram signals with high noise density.
It help our network can achive effectively prediction performance in the high noise communication environment.

MATLAB

Simulation result & network complexity comparison

Network	No.Layers	No.Params	G.Accuracy (%)	W.IoU (%)	M.BFScore (%)
SpecSenseNet	125	**7.8M**	**97.23**	**94.61**	**87.32**
U-Net [11]	59	31.3M	**98.22**	**96.53**	**90.56**
U-Netp [12]	101	42.5M	**98.07**	**96.24**	**89.20**
U-NetE [12]	101	42.3M	**97.84**	**95.82**	**88.05**
U-Netpp [12]	101	43.5M	**97.98**	**96.07**	**88.89**
ConvNet [8]	100	20.6M	39.69	19.32	15.61
Deeplabv3+ [9]	100	20.6M	42.26	33.87	14.39

[8] T. Huynh-The, Q.-V. Pham, T.-H. Vu, D. B. da Costa, and V.-P. Hoang,"Intelligent spectrum sensing with convnet for 5G and LTE signals identification," in Proc. IEEE Statistical Signal Processing Workshop (SSP), Hanoi, Vietnam, Jul. 2023, pp. 140–144.
[9] G.-V. Nguyen, C. V. Phan, and T. Huynh-The, "Accurate spectrum sens_x0002_ing with improved DeepLabV3+ for 5G-LTE signals identification," in Proc. 12th International Symposium on Information and CommunicationTechnology (SOICT), Ho Ch iMinh, Vietnam, Dec. 2023, pp. 221–227.
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[12] Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh, and J. Liang, "Unet++: Redesigning skip connections to exploit multiscale features in image segmentation," IEEE Transactions on Medical Imaging, vol. 39, no. 6, pp. 1856–1867, Jun. 2019.

Reducing significant network's parameters

Maintaining high prediction performance

MATLAB

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The number of layers increase because we repacle normal convolution to depth-wise sparable convolution (depth-wise conv + point-wise conv)

MATLAB

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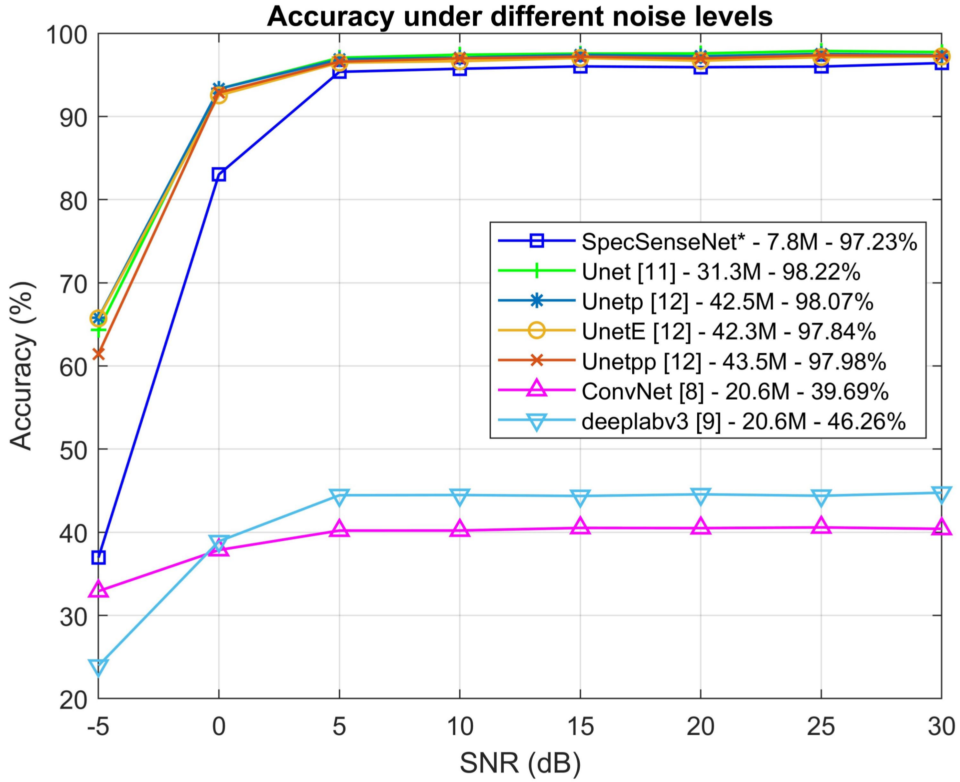
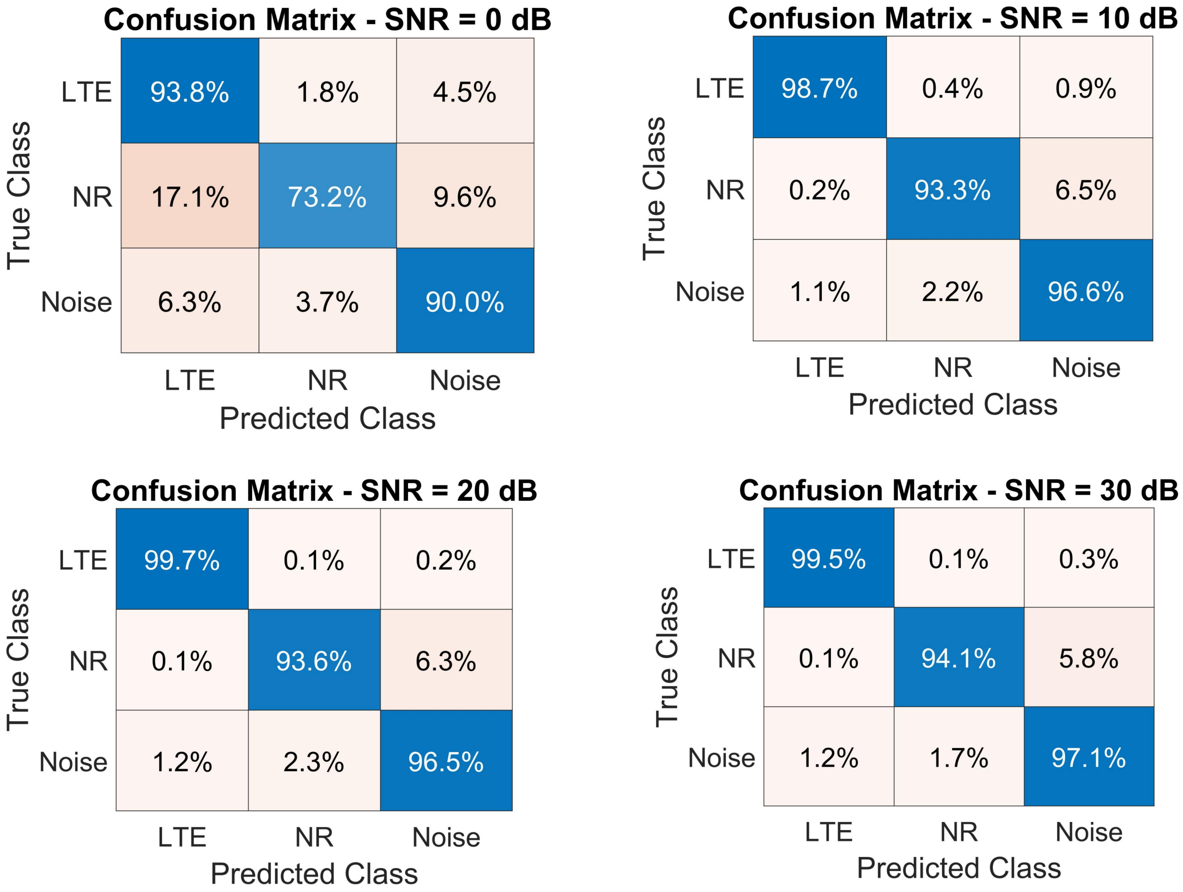
[12] Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh, and J. Liang, “Unet++: Redesigning skip connections to exploit multiscale features in image segmentation,” IEEE Transactions on Medical Imaging, vol. 39, no. 6, pp. 1856–1867, Jun. 2019.

Comparison with other networks



Confusion matrix when evaluating SpecSenseNet under variable SNR ranges



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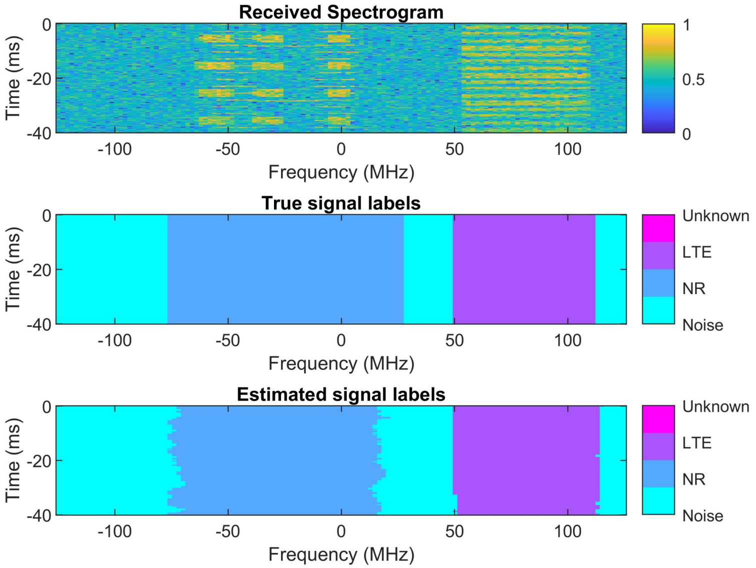
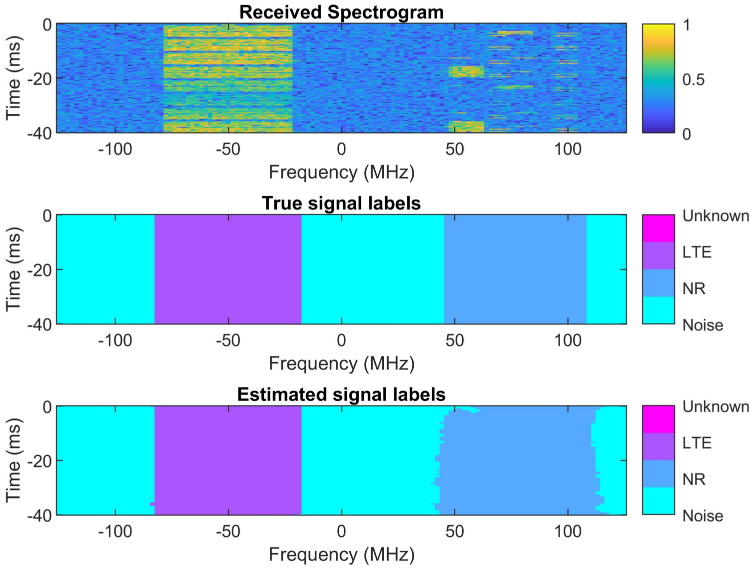
Visualization of received spectrograms in various SNR levels

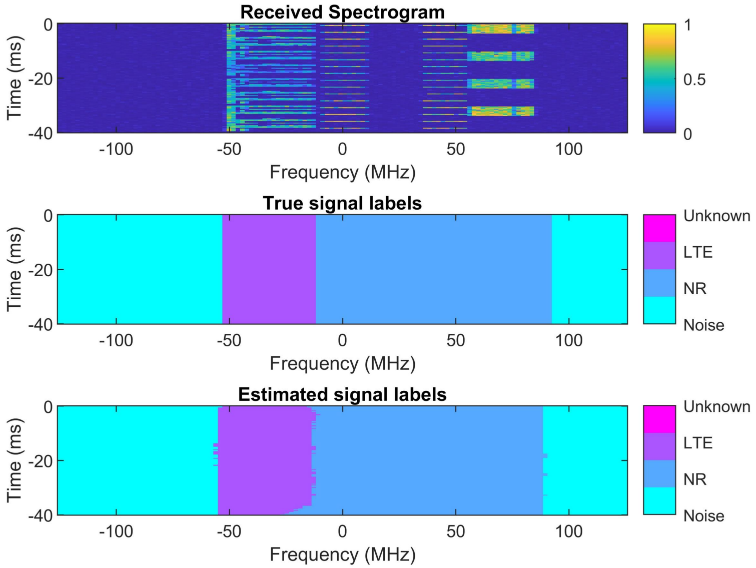
5 dB



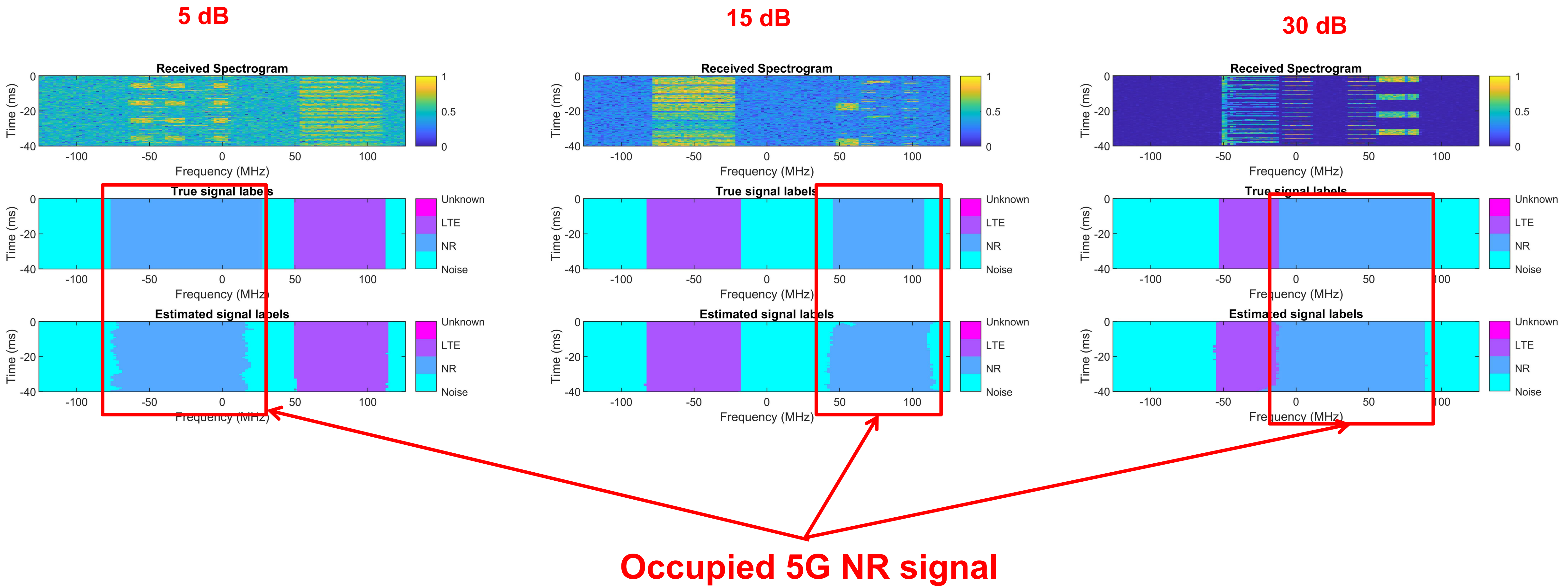
15 dB



30 dB

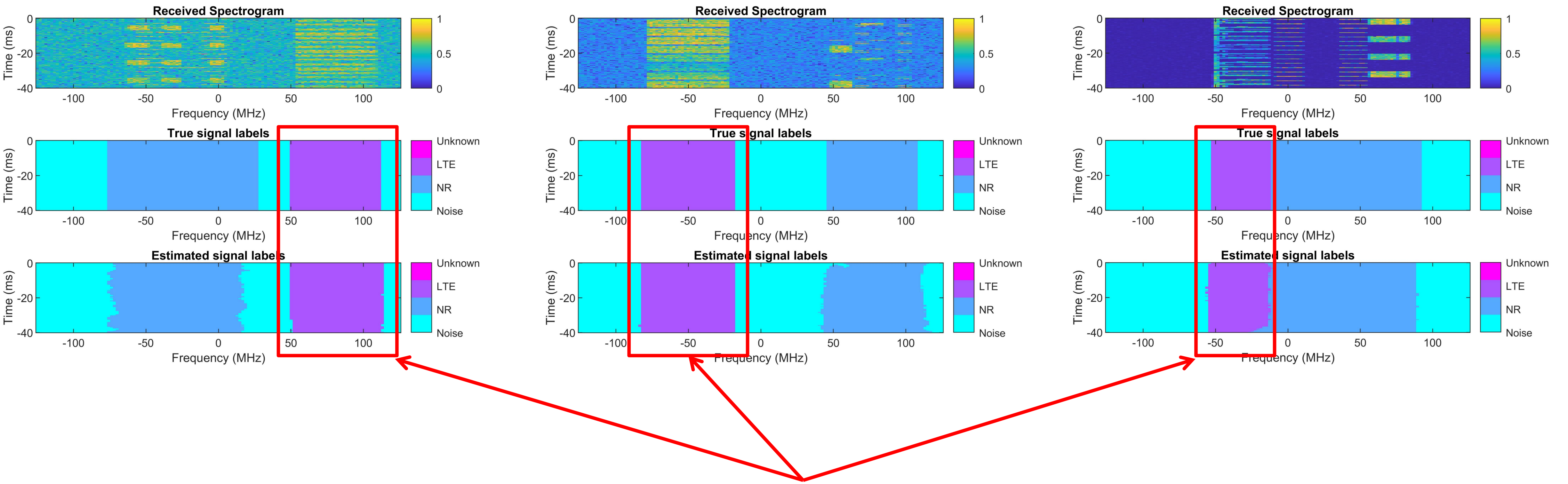


Visualization of received spectrograms in various SNR levels



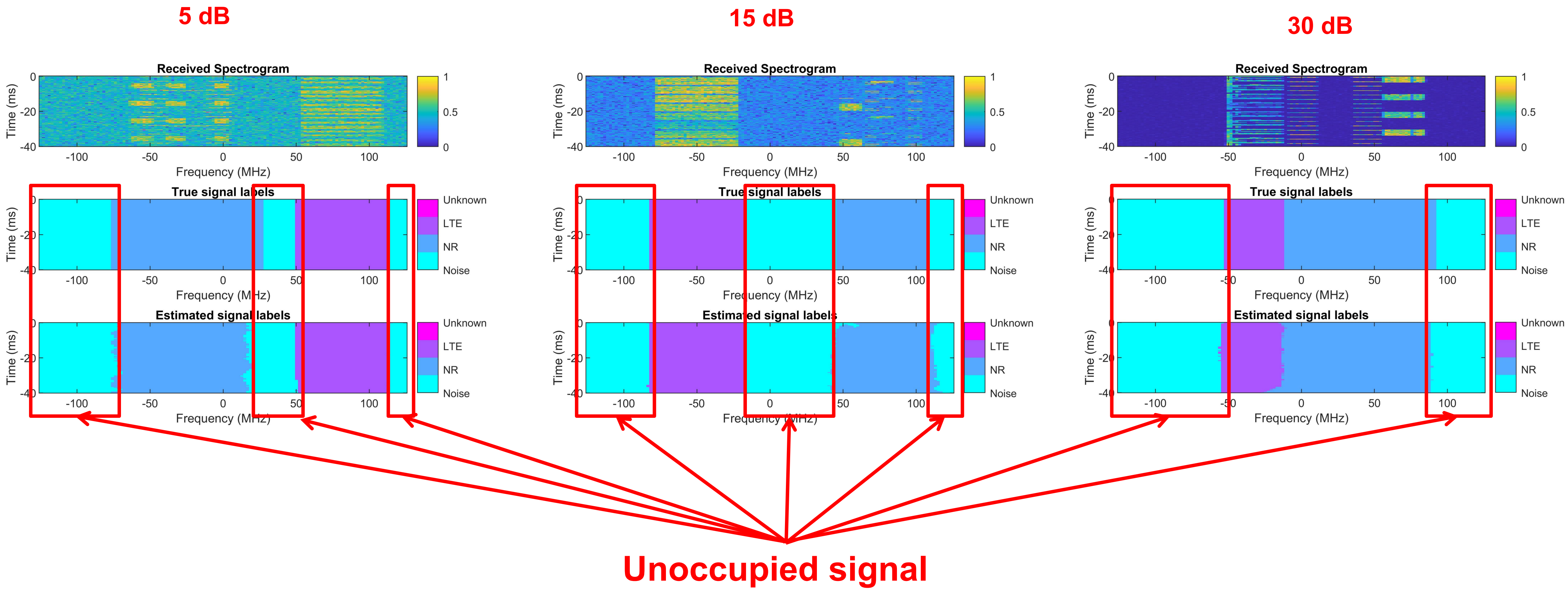
Visualization of received spectrograms in various SNR levels

5 dB **15 dB** **30 dB**



Occupied LTE signal

Visualization of received spectrograms in various SNR levels



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ATC 2024

2024 International Conference On Advanced Technologies For Communications

17 - 19, October, 2024, Ho Chi Minh City, Vietnam

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