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5G Channel Estimation Using Deep Learning

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Abstract
The abstract focuses on the integration of 5G channel estimation and the vulnerability of deep learning models, specifically in the context of OFDM signals, while employing a student-teacher model architecture. Channel estimation is a crucial aspect of 5G communication systems, ensuring reliable data transmission in dynamic wireless environments. Simultaneously, the advent of deep learning introduces susceptibility to adversarial attacks, where malicious inputs can deceive the model's predictions. This paper explores the intricate relationship between 5G channel estimation and deep learning vulnerabilities, emphasising the application of a student-teacher model to enhance system robustness. By delving into the nuances of OFDM signals, the study aims to provide a comprehensive understanding of how these elements intertwine, offering insights into potential security enhancements for next-generation wireless communication systems.

Keywords: Deep Learning, Channel Estimation, OFDM, Adversarial attacks, Malicious inputs

1. Introduction

The evolution of next-generation wireless networks, notably 5G and its successors, marks a revolutionary phase in telecommunications, characterised by unparalleled data speeds, ultra-low latency, and pervasive connectivity. At the heart of these advancements lies the critical task of channel estimation, a fundamental aspect ensuring the efficient and reliable transmission of data in the complex wireless communication environment. Orthogonal Frequency Division Multiplexing (OFDM) signals, integral to these networks, necessitate sophisticated channel estimation techniques for optimal performance.

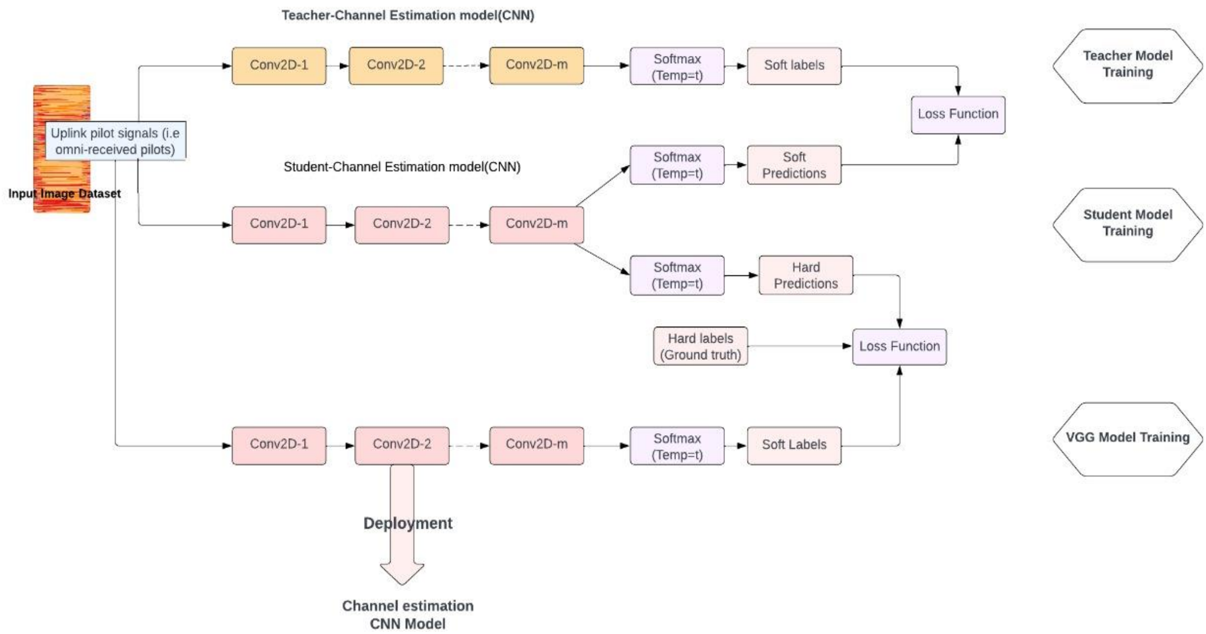
In recent years, Deep Learning (DL) has emerged as a potent tool in tackling the intricacies of channel estimation. DL-based models, such as the Student model, Teacher model, and VGG model, offer promising avenues for enhancing the accuracy and efficiency of channel estimation processes. These models leverage the power of artificial intelligence to learn and adapt to the dynamic characteristics of wireless channels, providing a robust foundation for the next generation of communication systems.

The integration of DL models into the fabric of 5G and beyond brings forth new security concerns, particularly in the face of adversarial attacks. Adversarial attacks, aimed at undermining the integrity and functionality of DL models, pose a significant threat to the reliability of channel estimation. The vulnerability of these models to attacks like Fast Gradient Sign Method (FGSM), Basic Iterative Method (BIM), Projected Gradient Descent (PGD), Momentum Iterative Method (MIM), and Carlini & Wagner (C&W) demands careful scrutiny.

This research paper embarks on a comprehensive exploration of the intersection between 5G channel estimation, OFDM signals, and adversarial attacks on DL-based models. The Student model, Teacher model, and VGG model serve as focal points for investigation, evaluating their susceptibility to adversarial threats and proposing mitigation strategies. As we delve into this dynamic landscape, our aim is to shed light on the opportunities and challenges arising at the nexus of cutting-edge communication technologies and the ever-growing imperative for robust security measures.

One of 5G's innovative strategies to reduce ISI and fading in a multipath environment is OFDM. OFDM is known for its high spectral efficiency & inherent immunity against ISI and multipath fading. High data rates are possible through adjusting modulation order or transmitted power individually according to channel response and noise background for each sub-band. Accurate channel estimation process should be engaged before and during the data transfer. Among the widely used channel estimation techniques is PACE, where a training sequence is used to modulate agreed upon subsets of OFDM carries.

2. Architecture diagram



3. Design and Implementation

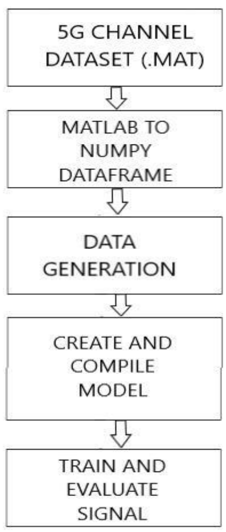


Fig 3.1

From the above figure fig.3.1 to implement the workflow for utilising a 5G channel dataset, start by loading and saving the dataset in MATLAB as a .mat file. Then, in Python, use tools like SciPy to load the .mat file, convert it into a NumPy array, and create a Pandas Data Frame for further manipulation. Ensure consistency between the MATLAB and Python representations of the dataset. Following data loading and conversion, proceed to data generation. This involves preprocessing steps such as normalisation and handling missing values. Split the dataset into training and evaluation sets using tools like Scikit-learn, maintaining a representative distribution of data in each subset. Following data loading and conversion, proceed to data generation. This involves preprocessing steps such as normalisation and handling missing values. Split the dataset into training and evaluation sets using tools like Scikit-learn, maintaining a representative distribution of data in each subset. With the prepared data, define a machine learning model using frameworks like TensorFlow or PyTorch. Design the model architecture based on the nature of the 5G channel dataset—whether it's a regression or classification task. Train the model on the training set, adjusting hyperparameters as needed, and monitor its convergence.

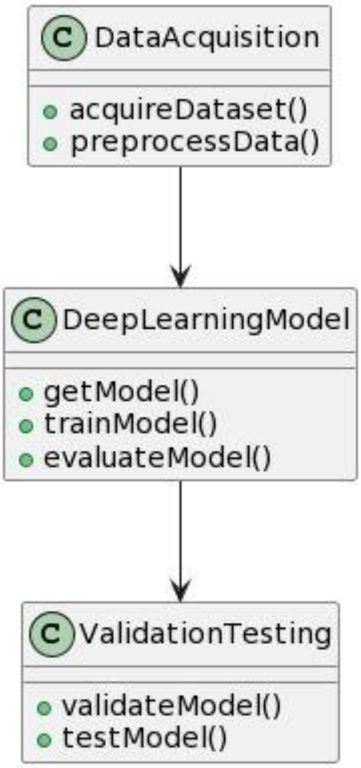


Fig 3.2

From the above figure fig 2.2 the workflow involves initially saving a 5G channel dataset in MATLAB as a .mat file, followed by loading and converting it into a NumPy array and a Pandas Data Frame using SciPy in Python. The process ensures compatibility between MATLAB and Python representations. Subsequently, data generation steps involve preprocessing, normalisation, and splitting the dataset into training and evaluation sets, maintaining data distribution.

After data preparation, a machine learning model is defined using TensorFlow or PyTorch, tailored to the task—whether regression or classification—posed by the 5G channel dataset. The model is trained on the training set, with potential adjustments to hyperparameters for optimal performance. Evaluation is conducted on a separate set, employing relevant metrics, and the model is refined based on the results. Attention is given to dataset-specific features and labels throughout the workflow, ensuring the model captures essential patterns. This integrated approach leverages the strengths of both MATLAB and Python for effective data handling and machine learning model development.

4. Methodology

In the methodology, 5G channel estimation is addressed through an intricate analysis of pilot-based methods and machine learning techniques. Pilot signals, composed of known symbols, play a pivotal role in channel estimation. The study delves into the deployment of pilot symbols within the OFDM framework, utilising their known characteristics to infer channel conditions accurately. Machine learning, particularly leveraging deep learning models such as the VGG model, is then introduced to augment the precision of channel estimates. The integration of a student-teacher model architecture further fortifies the system's robustness. The student model assimilates insights from the teacher model, which encapsulates domain knowledge, optimising the channel estimation process based on the received pilot signals. To comprehensively assess the system's resilience, adversarial attacks are explored, introducing carefully crafted malicious inputs designed to exploit potential vulnerabilities. This involves a nuanced examination of the interplay between the student and teacher models, with a focus on safeguarding against adversarial threats in the context of 5G channel estimation, particularly in the presence of pilot signals.

5. Dataset description with channel parameters

In this study, the MATLAB 5G Toolbox serves as a comprehensive resource, offering diverse reference examples for next-generation communication systems, particularly in the context of 5G networks. The focus lies on utilising the toolbox's capabilities to tailor and generate datasets for deep learning (DL)-based models, specifically in channel estimation. The dataset is produced through the "Deep Learning Data Synthesis for 5G Channel Estimation" reference example, employing a convolutional neural network (CNN) for channel estimation. Leveraging single-input single-output (SISO) antenna methods, the example utilises the physical downlink shared channel (PDSCH) and demodulation reference signal (DM-RS) to create the training datasets. These datasets consist of 256 instances, each comprising 8568 data points transformed into real-valued 612-14-2 matrices to suit CNN input requirements. The 4-D arrays, encompassing various channel characteristics, facilitate effective training of the CNN-based channel estimation model. The MATLAB 5G Toolbox's flexibility extends to tuning communication channel parameters, offering a versatile platform for experimentation and model optimization.

Channel Parameter	Value
Delay Profile	TDL-A, TDL-B, TDL-C, TDL-D, TDL-E
Delay Spread	1-300 ns
Maximum Doppler Shift	5-400 Hz
NFFT	1024
Sample Rate	30720000
Symbols Per Slot	14
Windowing	36
Slots Per Subframe	2
Slots Per Frame	20
Polarization	Co-Polar
TransmissionDirection	Downlink
NumTransmitAntennas	1
NumReceiveAntennas	1
FadingDistribution	Rayleigh
Modulation	16QAM

Table1: Channel estimation parameters with values

6. CNN models using channel estimation

Here, the model defines a convolutional neural network with three convolutional layers, where the number of filters and activation functions can be adjusted using the mult_factor parameter. This function provides flexibility in creating different variations of the model for experimentation. 3 CNN models have been used namely

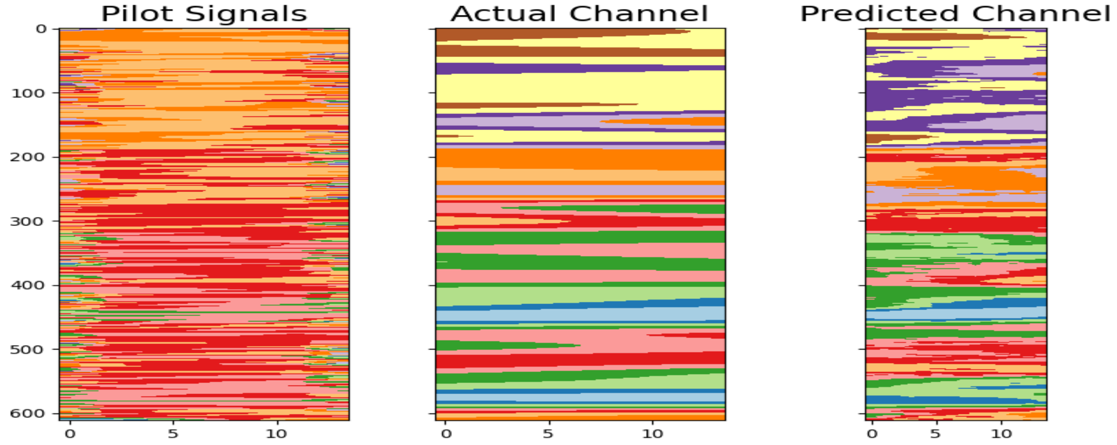
A. Student model

B. Teacher model and

C. VGG model.

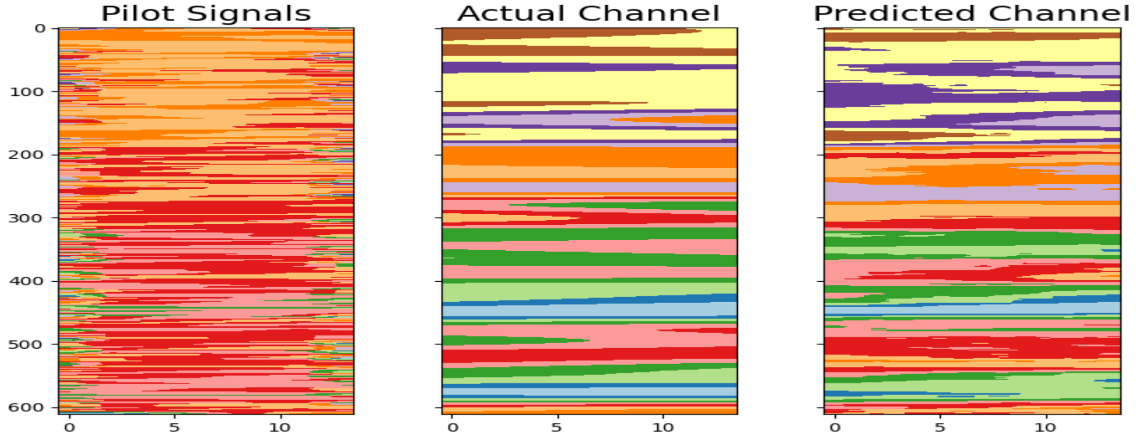
A. Student model:

Student model defines and trains a knowledge distillation process using a distiller model, incorporating a student model (student_model) and a teacher model (teacher_model). The distillation optimises a composite loss function, balancing mean squared error (MSE) and Kullback - Leibler divergence (KL Divergence). The training is controlled by early stopping with a patience of 150 epochs to prevent overfitting. The process aims to transfer knowledge from the teacher to the student model, enhancing the student's performance on the given task. The training progress is tracked through the hist_distill history object.



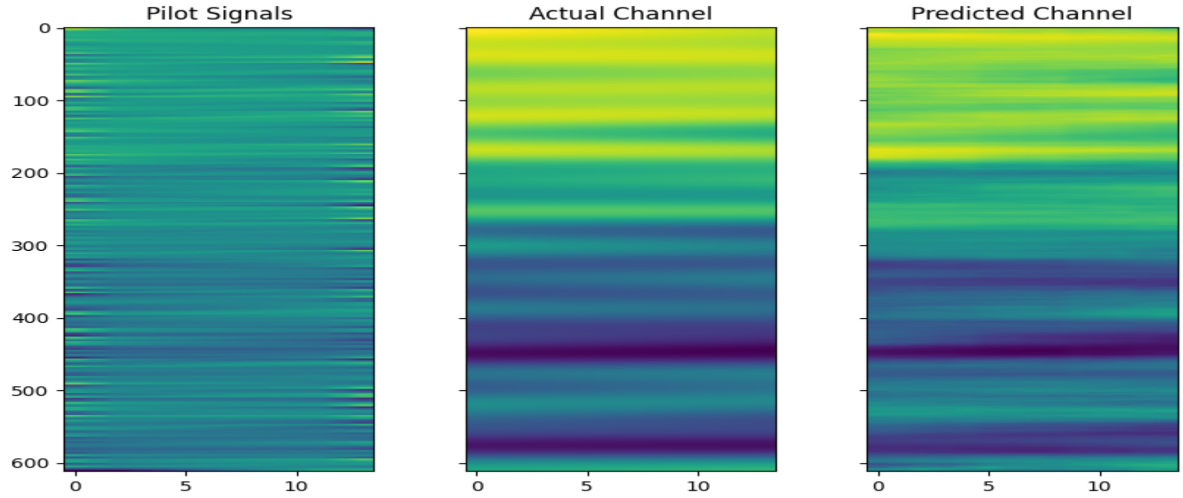
B. Teacher model:

Teacher model's evaluate performance on a test input. The teacher model takes test_input1 and predicts a channel output (pred). The figure displays three subplots: the first subplot represents pilot signals, the second shows the actual channel derived from real_output1, and the third displays the predicted channel. The teacher model is not explicitly provided in the code, but it is expected to be a neural network trained for channel prediction, with its architecture and details influencing the displayed predictions.



C.VGG model:

The VGG-16 model consists of three convolutional layers. The first layer has 48 filters of size 9x9 with SELU activation, followed by a layer with 16 filters of size 5x5 and Softplus activation. The final layer has one filter of size 5x5 with SELU activation. The model is designed for processing input images with dimensions (612, 14, 1). It is compiled using the Adam optimizer and mean squared error (MSE) loss. Early stopping with a patience of 50 epochs is employed to prevent overfitting during training.



7. Performance evaluation using MSE

In assessing and comparing convolutional neural network (CNN)-based models, the Mean Squared Error (MSE) serves as a key performance metric. This metric, expressed by the MSE equation , quantifies the average squared discrepancy between actual values (hi) and their corresponding predictions (h^i). The calculation involves summing the squared differences across all instances (t) and dividing by the total number of instances (n). A lower MSE signifies reduced model error, approaching zero when predictions precisely match actual values. As MSE increases, it indicates an escalating disparity between predicted and actual outcomes, serving as a crucial measure for model evaluation and further analysis in the research context.

$$MSE = 1/N \sum_{i=1}^{N} (\hat{h}_i - h_i)^2$$

8. Graph Comparison Statistics

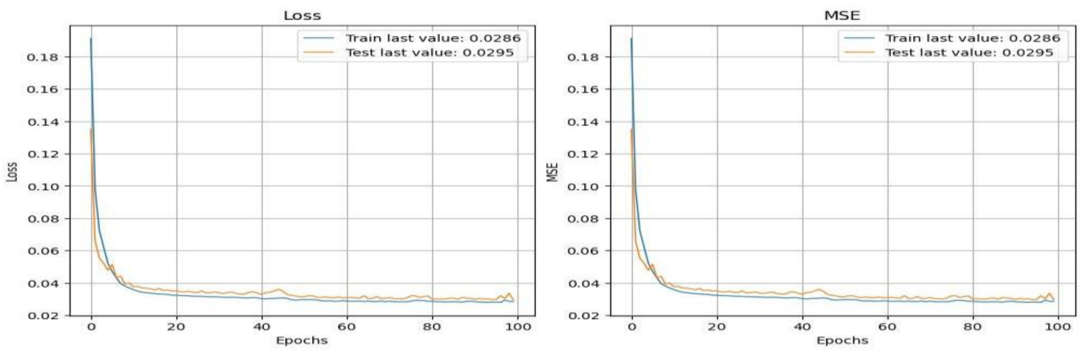


Fig 8.1: The student model displays the loss and mse(accuracy) values shown in the above graph with respect to various epochs

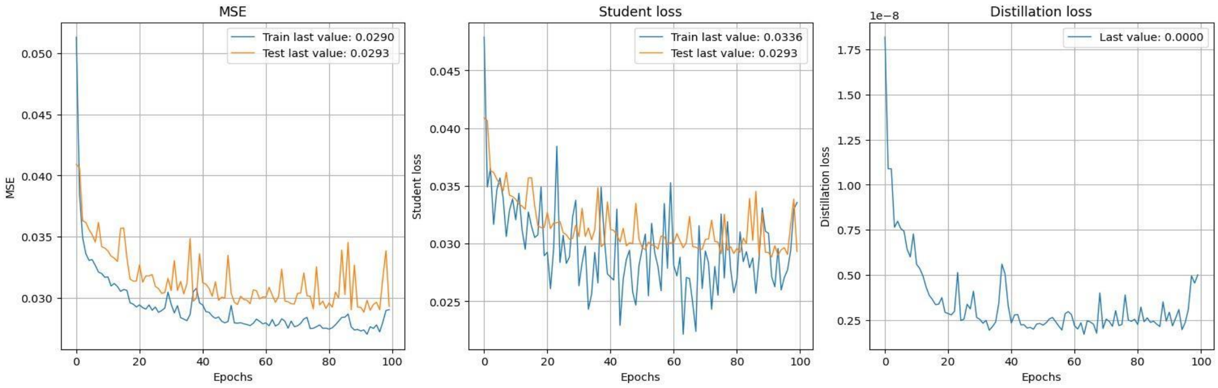


Fig 8.2: The teacher model displays the mse, student loss, distillation loss in the above graphs with respect to various epochs.

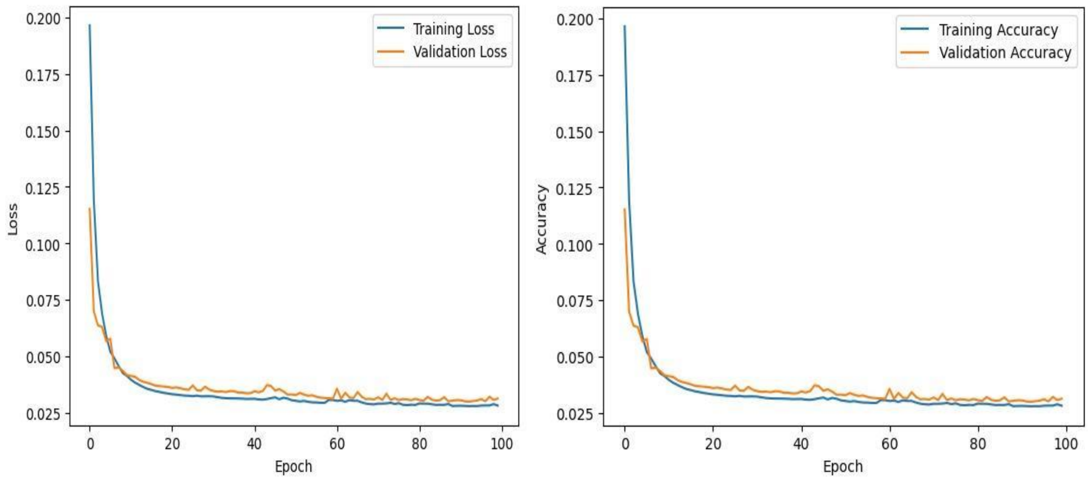


Fig 8.3: The VGG model displays the loss and accuracy in the above graph with respect to various epochs.

9. Simulation Results:

	Malicious_Distance	Real_Predicted_MSE	Malicious_Predicted_MSE	MalOut_RealOut_Diff	Attack	eps
949	2.800012	0.045292	0.046627	0.944371	BIM	0.5
604	1.400000	0.050892	0.051289	0.446116	FGSM	1.0
505	2.800034	0.099179	0.099507	0.481642	BIM	3.0
1040	2.800000	0.023516	0.023339	0.784732	PGD	0.5
842	0.140000	0.015525	0.015505	0.050188	FGSM	0.1
457	2.800002	0.037142	0.038506	0.789297	BIM	1.0
88	2.800003	0.049513	0.050062	0.760403	PGD	3.0
484	1.400000	0.032067	0.032188	0.476651	FGSM	1.0
236	0.140001	0.016300	0.016301	0.035943	FGSM	0.1
429	0.140000	0.029727	0.029741	0.044882	FGSM	0.1

It demonstrates how to generate adversarial examples using different attack methods and epsilon values. It then evaluates the model's performance and vulnerability to these adversarial inputs by comparing the

model's predictions on the original and adversarial examples. The results are stored in various lists for further analysis and evaluation.
In the context of 5G channel estimation employing deep learning, the susceptibility to adversarial attacks with malicious inputs poses a critical challenge. Diverse attack methodologies, including Fast Gradient Sign Method (FGSM) and Projected Gradient Descent (PGD), can strategically manipulate input data to deceive deep learning models. These adversarial inputs aim to introduce subtle perturbations, leading to erroneous channel estimations. Understanding and mitigating the impact of such attacks are crucial for ensuring the robustness and reliability of deep learning models in 5G environments. Investigating susceptibility to adversarial inputs and devising effective countermeasures are essential components in fortifying the security and trustworthiness of deep learning-based solutions for 5G channel estimation.

10. Conclusion

In conclusion, this study illuminates the escalating vulnerabilities of deep learning(DL) Based channel estimation models within the dynamic landscape of rapidly advancing mobile wireless communication networks, particularly in the context of NextG networks. The susceptibility of the original DL-based model to adversarial attacks, notably BIM, MIM, and PGD is underscored, with heightened attack success rates observed under intense adversarial conditions. However, the proposed defensive distillation-based mitigation method emerges as a promising avenue for bolstering model accuracy and resilience against higher-order adversarial attacks. The use of adversarial attacks suggests a proactive approach towards addressing security and reliability challenges in wireless communication systems.The significant reduction in the attack success rate, from 0.9 to 0.06, signifies the efficacy of the mitigation strategy. Looking forward, the authors aim to extend their research to encompass intelligent reflecting surfaces(IRS) and spectrum sensing using AI-based models, with a focus on unravelling and addressing potential cybersecurity risks in these emerging realms of technology.

11. References

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