A Deep Learning based Channel State Information Model for Future Generation High Speed Networks

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Abstract: Recently, the demand of high-speed electronic devices and gadgets have taken a drastic rise. Especially, the utilization of electronic devices like smartphones, tablets and smart watches are enhanced enormously over the last two decades. However, all these devices operates on internet and thus, mobile operators face a critical and complex challenge of providing high-speed internet facilities with customer satisfaction which is very challenging to achieve with the current available bandwidth spectrum utilization. Therefore, implementation of 5-th Generation (5G) Cellular Network is a quite decent solution to counter these challenges. However, there are several issues associated with 5-th Generation (5G) Cellular Network which can degrade their performance. Therefore, a Deep Learning-based Channel State Information (DLCSI) Model is introduced to enhance the efficiency of CSI prediction in ***massive*** Multiple Input Multiple Input (MIMO) system for effective bandwidth spectrum utilization in 5-th Generation (5G) Cellular Network. The proposed DLCSI model efficiently reduces channel overhead and enhances efficiency of CSI estimation based on deep learning methods. Cloud technology can provide immense strength to implementation of 5G wireless cellular network by providing their exceptional resource pooling capabilities and high storage capacity. Furthermore, the proposed DLCSI model outperforms all the state-of-art-CSI estimation techniques and effectively reconstruct CSI which provides strength to massive MIMO system for 5G cellular network implementation considering performance matrices like NMSE, Correlation factor, CSI estimation accuracy.

Keywords: Channel State Information (CSI), Deep Learning Techniques, 5-Generation (5G), *massive* Multiple Input Multiple Input (MIMO), Cloud Technology

1 Introduction:

Over the last three decades, Cloud Computing technology have made a significant impact on several industries such as information technology, communication, healthcare, education, banking, manufacturing, entertainment and many more. Moreover, recent technology developments in information and communication fields provide maximum yield in coordination with Cloud Computing technology due to its on-demand and cost effective resource access facilities. Hence, the significance of cloud computing technology has widely emerged in these fields due to it offers some exceptional facilities like resource pooling capabilities, on-demand resource access, virtualization, high elasticity, pay-per-use model and multitenancy without any substantial management issues. Besides, these functionalities provide immense strength to Communication and Information Technology industries for finding new solutions and technology developments in providing a cost-effective, flexible, robust and powerful mobile communication network [1]. Furthermore, the extensive utilization of cloud computing services in the fields of gaming, healthcare, entertainment, news, business and social networking applications have grown interest of several mobile communication network operators to provide a superfast and high bandwidth fifth-generation (5G) mobile network with greater flexibility and scalability by designing innovative and improvised services to fulfil the market expectations.

Moreover, present wireless network are battling with heavy traffic demands and high data speed challenges due to widespread utilization of cloud-based functionalities and Internet of Services (IoS) to the end users. However, it is concluded that from a research survey that there will be an enhancement of 13 times in mobile data requirement in the next five years which is enormously high. Therefore, mobile operators are facing a critical challenge to meet these demands and expectations in near future. Thus, mobile network operators are taking significant steps in implementing fifth generation (5G) mobile network with advanced capacity and coverage capabilities in real-time [2]. Wireless communication network, Internet of things (IoT), cloud-based services and big-data solutions can operate together in single stream to develop a considerable solution for 5^{th} Generation (5G) mobile network [3].The 5G mobile network will provide large bandwidth spectrum, lower latency, high energy-efficiency, ultra-high mobile data rate, high throughput and extensive scalability. Therefore, adoption of cloud computing technology, Internet of things (IoT)and big-data solutions in 5G mobile network evolution has gained interest of several academic and industry level researchers.

However, numerous challenges are encountered while implementation of 5G mobile network in real-time and the challenges are high power consumption, Spectrum allocation, network throughput, interference occurrence, effective resource pooling management system, development of advance security protection system etc. Thus, a precise coordination between cloud computing technologies, Internet of things (IoT) and wireless communication system is required in order to ensure efficient implementation of 5G mobile network. Furthermore, MILLIMETER-WAVE ($mmWave$) multiple-input and multiple-output (MIMO) technique is one of the most exceptional and emerging wireless communication strategy which enables utilization of large bandwidth spectrum, offer highinformation transmission rates and higher reliability [4-6]. Moreover, multi-user interference reduction and high network efficiency can be achieved using $mmWave$MIMO technique by placing numerous antennas together with a single source station in a distributed or centralized system [7-8]. However, the installation cost of large antenna array and high power consumption degrades their performance due the availability of a Radio Frequency (RF) medium at every antenna [9].

Moreover, the performance of $mmWave$ MIMO technique is extensively depends upon Channel State Information (CSI) at source station. However, the proficient prediction of Channel State Information (CSI) is very critical when large number of radio-frequency medium are placed at every antenna in $mmWave$ MIMO system. The CSI for downlink medium usually acquired through feedback medium rather than direct estimation at source station in a frequency division duplex (FDD) model. Furthermore, more the number of the antenna more will be the amount of feedback which can enhance the overhead of $mmWave$ MIMO system [10]. Thus, several researchers and experts have made their efforts in providing solutions for these challenges and enhance throughput of $mmWave$ MIMO system. Some of the literatures are as follows. In [10], a deep learning methods are adopted for Channel State Information (CSI) feedback estimation based on the $mmWave$ MIMO system. This technique enhances throughput of channel feedback and CSI estimation.In [11], an artificial intelligence system is adopted for providing better Quality of Service (QoS) and ultra-high data rate so that the efficient implementation and optimization of 5G technology can take place. The advantages and challenges of 5G technology are highlighted comprehensively and their proficient solutions are discussed as well. In [12], a detailed survey is presented for 5G wireless cellular network based on the $mmWave$ MIMO system in order to discuss characteristics and challenges of 5G technology. This article also discusses about the radio-frequency (RF) spectrum and limitations of $mmWave$ MIMO system. Several solutions to avoid these limitations are mentioned as well. In [13], a detailed study is conducted over 5G mobile network and their implementation technologies. Here, several performance factors are discussed which can enhance spectrum efficiency and reduce power consumption in 5G mobile network. The $mmWave$ MIMO system is discussed as a proficient solution for 5G technology.

All the above mentioned literatures have considered that the$mmWave$ MIMO system is an efficient solution for the implementation of 5G wireless cellular network in real-time. However, the solutions provided for effective channel estimation are far away from practical implementation and the possibilities of designing better CSI prediction strategies are very high. Therefore, a Deep Learning-based Channel State Information(DLCSI) Model is adopted in this literature for precise critical CSI prediction based on the effective $massive$ Multiple Input Multiple Input (MIMO) system. The DLCSIModel effectively reduces the CSI overhead and acquire proper CSI at base station which can enhance throughput and reduce high interference causes due to large antenna array utilization in $massive$ MIMO system. The proficient coordination between $massive$ MIMO system and cloud technology can provide immense strength to implementation of 5G wireless cellular network as well. This technique is introduced to provide solutions for significant spectrum bandwidth utilization and enhance channel feedback efficiency. Cloud computing technology is adopted for their exceptional resource pooling capabilities and high storage capacity.Deep learning methods utilizes absolute and imaginary coefficients which is acquired from the correlation of upstream and downstream CSI components to achieve high speed processing. Deep learning techniques are employed to handle large datasetprocessing and study the underlying structures. The proposed DLCSI Modelensure high Quality of Service (QoS) and signal transmission accuracy. The performance of CSI estimation and feedback overhead is compared with various state-of-art- CSI methods based on several performance matrices.

This paper is arranged in following manner which are presented below. Section 2, discusses about the literatures review presented related to $massive$ MIMO system and their issues and how this issues can sorted using the proposed Deep Learning-based CSI Model (DLCSI). Section 3, mentions about the methodology used in proposed DLCSI for precise CSI prediction. Section 4 discusses about simulation results and their comparison with state-of-art- CSI methods and section 5 concludes the paper.

2 Related Work:

Over the last decade the utilization of smartphones, tablets and high-tech electronic gadgets are drastically enhanced in daily life. These electronic instruments are heavily utilized for essential private data storage to communication people on social networking sites. However, all these electronic devices are heavily depends upon internet. However, current mobile network companies are unable to deal with present market expectations and high mobile data demands due to heavy traffic all across world. Therefore, recent technology developments in wireless cellular networks and research experts have suggested implementation of 5G technology to handle these issues. Moreover, services of cloud computing technology can ensure dynamic resource pooling and immense storage capacity whereas Big Data Analytics can ensure effective real-time data processing. Therefore, the efficient coordination of Cloud Computing and Big Data solutions can provide immense strength to 5G cellular network in growing network access and improve spectrum utilization. However, implementation of 5G technology required a suitable model which can ensure high quality signal transmission and CSI estimation at source station. Thus, various researchers and experts have identified a $mmWave$ MIMO system as a potential solution. Therefore, some of the literatures are presented in this section to understand $mmWave$ MIMO system, their limitations and solutions to encounter them.

In [14], a deep learning based- $CsiNet$ technique is adopted for the estimation of CSI feedback based on the $massive$ MIMO system. Here, $CsiNet$ technique ensure significant channel estimation and reconstruction quality based on the CSI sensing and recovery model. The efficiency of the model is compared with conventional Compression Sensing (CS) methods. In [9], a deep learning based channel prediction method is introduced which depends upon $mmWave$ MIMO model. The deep learning algorithms are utilized to study channel structures and handle immense training data. An analytical framework is adopted for performance enhancement. In [15], a deep learning model is presented for application of wireless vehicular network. This technique reduces optimization problem and power consumption of wireless vehicular system. This technique ensures dynamic resource pooling and discuss their limitations as well. In [16], mm-Wave massive MIMO model is introduced for proficient channel state information estimation. Moreover, a hybrid analog-digital antenna mechanism is adopted to study the perceptions of analog and digital beamforming. In [17], mm-Wave Massive MIMO system is adopted for channel state information estimationwith the help of Sparse Channel prediction method. This technique provide strength to effective downlink transmission of signals. The channel sparsity is exploited using enhance channel predictor. In [18], a detailed research study is presented for effective resource sharing in ultra-dense systems such as massive MIMO & mm-Wave models, massive IoT applications and D2D systems etc. Their study limitations, problems and resolutions to reduce them are presented briefly.In [19], mm-Wave Massive MIMO model is adoptedto estimate CSI feedback and evaluate high compression ratio which depends upon Multiple-Rate Compressive Sensing methods. Here, Convolutional Neural Network (CNN) is introduced to achieve high quality signal restoration.In [20], a $Millimeter$ wave (mm-Wave) communication model is adopted based on the block sparse nature to evaluate efficient channel sparsity. Furthermore, Doppler shifts and parameter optimization is achieved using low-rank structures. This technique is adopted to ensure significantsignal restoration efficiency by exploiting channel sparsity.

As mentioned in the above literatures, several researchers and experts have provided their views and suggested utilization of techniques like Convolutional Neural Network (CNN) and deep learning methods in coordination with massive MIMO & mm-Wave systems. However, several issues like low spectrum throughput, high interference, channel overhead, critical path loss and low signal quality need to be addressed very soon for effective implementation of 5G cellular network in real-time. Therefore, a Deep Learning-based Channel State Information (DLCSI) Model is presented in this article for precise critical CSI prediction based on the effective $massive$ Multiple Input Multiple Input (MIMO) system.The proposed DLCSI model works accurately in coordination with wireless communication system, cloud computing technology and IoT applications. Deep learning based CSI model can increase poor channel estimation. Moreover, low-power, dense and small-antennas are employed to manage signal transmission rate in 5G technology to increase channel throughput and transmission efficiency. Next section discusses about the mathematical representation of DLCSI Model.

3 Modelling ofDeep Learning-based Channel State Information (DLCSI) Model:

This section discusses about the mathematical modelling of Deep Learning-based Channel State Information (DLCSI) Model. The CSI prediction is very critical and complex process which can degrade quality of transmission rate. However, a Deep learning based CSI model is presented to evaluate critical CSI prediction based on the effective $massive$ Multiple Input Multiple Input (MIMO) system. The massive MIMO system is adopted for efficient spectrum utilization and signal quality enhancement. The effective acquisition of downstream CSIis very essential at the source station (tSS) of wireless system in a timely manner to enhance spectrum efficiency. Furthermore, the acquisition of downstream CSI can take place with the help of Consumer Equipment (CE) which is required at the source station (tSS).

Assume that a massive Multiple Input Multiple Input (MIMO) system is adopted with a solo cell which contains a source station (tSS) with $R_d \gg 1$ associated antennas. The massive MIMO system also contains a Consumer Equipment (CE) with a solitary antenna. The Orthogonal Frequency Division Multiplexing (OFDM) is employed in this massive MIMO system for R_h subcarriers. Here, the acquired downstream signal at $x-th$ subcarrier is evaluated as,

$$k_c{}^{(x)} = g_c{}^{(x)M} . y_N{}^{(x)} . q_c{}^{(x)} + x_c{}^{(x)}, \tag{1}$$

Here, $q_c{}^{(x)} \in \mathbb{V}$ is represents the broadcasted signal and broadcasted beam former is represented by $y_N{}^{(x)} \in \mathbb{V}^{(R_d \times 1)}$. Moreover, the medium vector for $x-th$ subcarrier is expressed by $g_c{}^{(x)} \in \mathbb{V}^{(R_d \times 1)}$ and $x_c{}^{(x)} \in \mathbb{V}$ is represented as the noise associated with the broadcasted signal. Where, conjugate displacement is shown by$(\cdot)^M$. Likewise, the acquired upstream signal at $x-th$ subcarrier is evaluated as,

$$k_z{}^{(x)} = y_B{}^{(x)M} . g_z{}^{(x)} . q_z{}^{(x)} + x_z{}^{(x)} . y_B{}^{(x)M}, \tag{2}$$

Where, broadcasted signal collection is achieved using receiver beam former which is utilized to evaluate the direction of incoming broadcasted signal and denoted by $y_B{}^{(x)} \in \mathbb{V}^{(R_d \times 1)}$ and $x_z{}^{(x)} \in \mathbb{V}$ is represented as the noise associated in signal of upstream channel. For any spatial frequency domain, the upstream CSI components are expressed by following equation,

$$\widetilde{M}_z = \left[g_z{}^{(1)}, \dots \dots \dots .., g_z{}^{(R_h)}\right]^M \in \mathbb{V}^{(R_h \times R_d)} \tag{3}$$

Likewise, for any spatial frequency domain, the downstream CSI components are expressed by following equation,

$$\widetilde{M}_c = \left[g_c{}^{(1)}, \dots \dots \dots .., g_c{}^{(R_h)}\right]^M \in \mathbb{V}^{(R_h \times R_d)} \tag{4}$$

Here, the downstream CSI feedback system remains the focal research area of this literature. Therefore, consider that the source station (tSS) smoothly obtain upstream CSI component $\widetilde{M}_z$. Similarly, the Consumer Equipment (CE) smoothly obtain downstream CSI component$\widetilde{M}_c$. From equation (4), the downstream CSI component$\widetilde{M}_c$ is belongs to $R_h \times R_d$ i.e. $\widetilde{M}_c \cong R_h \times R_d$. However, R_d carries large value which can enhance feedback overhead of massive MIMO system. Then, an essential property of wireless system is exploited to mitigate the feedback overhead of massive MIMO system which implies that CSI matrices demonstrates some sparse nature in spatial delay domain for upstream and downstream CSI component. Then, conversion of medium response matrices take place from frequency domain $M_h$to time domain $M_\lambda$with the help of Inverse Discrete Fourier Transform (IDFT) which is demonstrated in following equation,

$M_h A^M = M_\lambda$	(5)

Where, $A \in R_d \times R_d$represents solitary DFT matrix. When Inverse Discrete Fourier Transform (IDFT) is applied to matrix $M_\lambda \in R_h \times R_d$ in time domain then all the elements of this matrix approaches to zero apart from the elements of first row$\hat{R}_h$. When IDFT applied to matrix M_λ, then the elements$\widetilde{M}_z$ and$\widetilde{M}_c$ of first row $\hat{R}_h$ are converted into C_v and C_b respectively. However, the feedback overhead $\hat{R}_h \times R_d$ of downstream CSI component remains very high. Thus, the compression of downstream CSI componentcan take place at Consumer Equipment (CE) side from inverse downstream CSI matrix M_c.

Furthermore, the compression of CSI feedback signal is achieved using an encoder whereas decoder is utilized to restore high quality signal. The channel overhead in downstream CSI feedback can be mitigated by compressing broadcasted signals and encode them into a low bit order. Moreover, state-of-art techniques$CsiNet$ and $DualNet-Mag$ utilizes only encoder and decoder for downstream CSI feedback compression and restore the broadcasted signals respectively. However, the proposed DLCSI Model utilizes a quantization system between encoder and decoder to compress the broadcasted signals, quantize them with the help of quantization block and then reconstruct the original broadcasted signals. Thus, the downstream CSI feedback model contains three action blocks such as compression block, quantization block and reconstruction block. The proposed DLCSI model optimizes downstream CSI feedback estimation by combining compression and quantization process at CE whereas signal reconstruction take place at tSS as shown in figure 1. Then, consider that $\widehat{M}_c$ represents the restored downstream CSI feedback matrix and quantization block function is denoted by $h_j(\cdot)$. Then, compression block, quantization block and reconstruction block using proposed DLCSI Model are represented in the following equation respectively for downstream CSI feedback,

$e_1 = h_{f,1}(M_c)$	(6)
$\hat{e}_1 = h_{j,1}(e_1)$	(7)

$\widehat{M}_c = h_{i,1}(\hat{e}_1)$	(8)

Similarly, compression block, quantization block and reconstruction block using proposed DLCSI Model are represented in the following equation respectively for upstream CSI feedback,

$e_2 = h_{f,2}(M_c)$	(9)
$\hat{e}_2 = h_{j,2}(e_2)$	(10)
$\widehat{M}_c = h_{i,2}(\hat{e}_2, M_z)$	(11)

Then, the optimization of in downstream CSI feedback is achieved by reducing the following equation,

$\left\Vert M_c - \widehat{M}_c \right\Vert^2$	(12)

Where, $\Vert\cdot\Vert$ is denoted as $Frobenius$ normalization. Here, the quantization process is a rounding method which is utilized for rounding off the input signal values into nearest output signal values of a finite set. The amplitude of CSI feedback components are optimized to become limited between$[e_{max}, e_{min}]$. Consider that number of bits used for amplitude quantization process is denoted by p. Then, every amplitude of CSI feedback components is evenly quantized into 2^p levels. Thus,

$\hat{e} = \triangle \lfloor e.(\triangle)^{-1} \rfloor$	(13)

Where, $\triangle$ is represented as $\triangle = [e_{max} - e_{min}].[2^p - 1]^{-1}$. Here, even quantization is performed using proposed DLCSI model for CSI feedback components. First of signal is compressed by training the CSI feedback component matrix with the help of proposed DLCSI model and then even quantization is applied on resultant CSI feedback component matrix and then quantized CSI feedback component matrix is fed to the reconstruct block of decoder for the restoration of CSI feedback component matrix as shown in figure 1.

The proposed DLCSI Model helps to reduce downstream CSI feedback load and efficiently estimate downstream CSI components. Deep learning methods ensure high-speed processing while estimating CSI components. The deep learning methods are utilized to handleabsolute and imaginary coefficients which is acquired from the correlation of upstream and downstream CSI components. The CSI feedback matrices are employed for fixing correlation between upstream and downstream CSI components. The CSI feedback matrices are optimized by attaining their correlation parameters in time domain. However, nature wise upstream and downstream CSI components remains complex. Therefore, absolute and imaginary coefficients are correlated separately. However, the acquired correlation parameter from absolute and imaginary coefficients is found inconsistent for upstream and downstream CSI feedback components. Furthermore, it is concluded from the result of Frequency Division Duplex (FDD) mechanisms that, out of phase and magnitude function, phase shows lower correlation than magnitude in time domain. Thus, phase and magnitude function are correlated separately in time domain to acquire upstream and downstream CSI components. The correlation coefficient considering magnitude shows larger value whereas the correlation coefficient consideringphase shows lower values for both upstream and downstream CSI components. Furthermore, absolute coefficients shows larger correlation values and lower correlation reported while considering their signs.

Thus, the proposed DLCSI Model in contrast to various conventional techniques discretely feeds back the absolute and imaginary coefficients with their signs. The most essential and crucial phase for the reduction of CSI feedback overhead is back transmission of uncorrelated information of upstream and downstream CSI feedback components with their signs.

The crucial functionality of the proposed DLCSI Model is the employment of fully linked layer size and feature map quantity. The values of fully linked layer size and feature map quantity becomes double when upstream and downstream CSI feedback components are utilized in terms of absolute and imaginary coefficients. From the above mentioned details it is considered that the phase function with their signs ae encoded at Consumer Equipment (CE) due to their lower value of correlation coefficient. In contrast, feedback obtained at CE and upstream CSI components is jointly utilized for decoding the downstream CSI components at source station (tSS). It is evident that the proposed DLCSI Model provides high performance throughput in terms of downstream CSI feedback overhead and signal restoration efficiency. The utilization of quantization block reduces downstream CSI feedback overhead significantly for a massive MIMO system. The impact of quantization block on signal restoration efficiency is very huge.

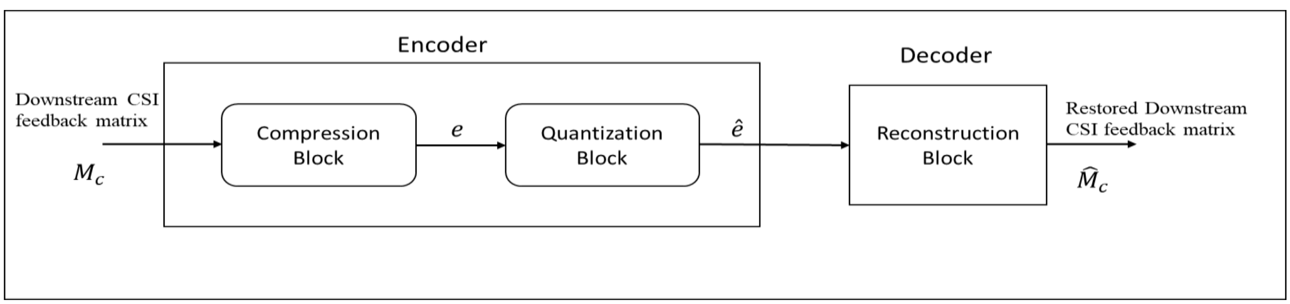

Figure 1 Block Diagram of Proposed DLCSI Model

4 Performance Evaluation:

This section discusses about the performance comparison of proposed Deep Learning-based Channel State Information (DLCSI) Modelwith other state-of-art-techniques in terms of compression ratio, Normalized Mean Square Error (NMSE), reconstruction accuracy and correlation between upstream and downstream CSI components. Furthermore, a detailed investigation over massive Multiple Input Multiple Output (MIMO) system is presented to evaluate the impact DLCSIModelon reconstruction efficiency. This article provides a detailed investigation on state-of-art CSI estimation techniques and challenges faced by them and ensure significant solutions to mitigate them. The proposed DLCSIModel enhances channel estimation efficiency of massive MIMO system by reducing channel overhead and interference between antenna array elements. The proposed DLCSI model induces proper coordination between $massive$ MIMO system and cloud technology to enhance bandwidth spectrum utilization for the implementation of 5G wireless cellular network.

The dataset utilized in this article to simulate performance results is taken from [21]. The performance results obtained from COST 2100 MIMO channel model [22] using proposed DLCSI model are fairly compared with original $CsiNet$ and the normalized $CsiNet$ in feedback channel [10].Thus, deep learning techniques are employed to handle such large dataset which consists of thousands of training samples and to study the underlying structures. Furthermore, deep learning techniques ensure high efficiency for the CSI estimation in comparison with other conventional techniques. Deep learning techniques ensure exceptional performance improvement in reduction of CSI matrix dimensions which enhances compression efficiency. This dataset is segregated in two types of rural scenarios in which, one represent indoor CSI matrices and another represent outdoor CSI matrices. The carrier frequency of outdoor CSI scenario is set at 300 MHz and for indoor CSI scenario is set at 5.3 GHz. The number of subcarriers utilized are 1024 and 32 antenna array elements are placed at the transmitter side. Rest of the simulation parameter are kept similar as [22]. System parameters are optimized by training the proposed DLCSI model. The Normalized Mean Square Error (NMSE) is evaluated to measure signal restoration accuracy. Table 1 discusses about the NMSE (dB) Performance of Reconstructed CSIusing proposed DLCSI model in comparison with state-of-art- $CsiNet$ techniques. It is quite evident from Table 1 results that the proposed DLCSI model outperforms all the state-of-art- $CsiNet$ techniques for both indoor and outdoor scenarios. However, NMSE reduction is much higher in indoor scenario than in comparison with outdoor scenario. The CSI matrices for both indoor and outdoor scenarios are sparse in nature. The proposed DLCSI model concludes its superiority by outperforming $CsiNet$ as well as their improvised models $CsiNet - M1$ and $CsiNet - M2$ for different compression ratios as 4, 16 and 32 for both indoor as well as outdoor scenarios. The NSME performance improvement reduces as the compression ratio increases for all CSI estimation techniques. However, the restoration of signal loss is significantly enhanced using the proposed DLCSI model in all cases, especially for low compression ratio.

Table 2 discusses about the NMSE (dB) Performance of Reconstructed CSIusing proposed DLCSI model in comparison with several state-of-art- CSI estimation techniques. It is quite evident from Table 2 results that the proposed DLCSI model outperforms all the state-of-art- CSI estimation techniques for both indoor and outdoor scenarios.However, reconstruction accuracy enhancement is much higher in indoor scenario than in comparison with outdoor scenario using proposed DLCSI model. The proposed DLCSI model concludes its superiority by outperforming $CsiNet+$ as well as other state-of-art CSI estimation techniques such as Uniform Quantization (UQ), Non-Uniform Quantization (NUQ) and Non-Uniform Quantization (NUQ) with offset network (NUQ-O) for different compression ratios as 4, 16 and 32 for both indoor as well as outdoor scenarios. A significant improvement is achieved in signal loss reconstruction which is evident from Table 1 and Table 2 for all cases. Hence, the efficiency of Channel State Information (CSI) get enhanced significantly using proposed DLCSI model.

Here, Figure 2 demonstrates the correlation factor ρ performance evaluation as a function of compression ratio (γ) for proposed DLCSI model in comparison with various state-of-art-techniques considering indoor scenarios. The correlation factor ρ performance evaluationfor proposed DLCSI model considering outdoor scenario is also presented which shows correlation factor of indoor scenario performs better than outdoor scenario. However, the proposed DLCSI model outperforms state-of-art-$CsiNet$ techniques for both indoor and outdoor scenarios considering correlation factor ρ performance evaluation as a function of compression ratio(γ).Here, Figure 3 demonstrates the reconstruction accuracy enhancement curve in terms of NMSE as a function of compression ratio (γ) for proposed DLCSI modelin comparison with various state-of-art-techniques such as $\mathrm{CsiNet}+$ *and* $\mathrm{CsiNet}+/\mathrm{T}$ considering indoor and outdoor scenarios. Furthermore, Figure 4 demonstrates the reconstruction accuracy enhancement curve in terms of NMSE as a function of compression ratio (γ) for proposed DLCSI modelin comparison with various state-of-art-techniques such as$\mathrm{CsiNet}+$,CsiNet *and* JC_ResNet considering both indoor and outdoor scenarios. It is clearly evident from Figure 3 and figure 4 that the proposed DLCSI model outperforms all the state-of-art-CSI estimation techniques and effectively reconstruct CSI which provides strength to massive MIMO system for 5G cellular network implementation.

Table 1NMSE (dB) Performance of Reconstructed CSI

	CR	$CsiNet$	$CsiNet-M1$	$CsiNet-M2$	$DLCSI$
INDOOR	4	-17.36	-20.80	-24.80	-28.98
	16	-8.65	-11.77	-12.21	-19.47
	32	-6.24	-8.75	-8.65	-11.72
OUTDOOR	4	-8.75	-10.14	-10.78	-17.59
	16	-4.51	-4.99	-4.44	-7.41
	32	-2.81	-1.87	-2.78	-5.88

Table 2NMSE (dB) Performance of Reconstructed CSI

	CR	$CsiNet+$	UQ	NUQ	$NUQ+O$	$SM-CsiNet+$	$PM-CsiNet+$	$DLCSI$
	4	-27.37	-18.40	-20.08	-20.35	-27.90	-27.60	-28.98

INDOOR	16	-14.14	-12.27	-12.64	-12.68	-13.45	-12.25	-19.47
	32	-10.43	-9.07	-9.40	-9.43	-9.89	-8.24	-11.72
OUTDOOR	4	-12.40	-10.54	-11.21	-11.68	-11.91	-12.02	-17.59
	16	-5.73	-5.00	-5.31	-5.47	-5.31	-5.07	-7.41
	32	-3.40	-3.05	-3.00	-3.10	-3.22	-3.00	-5.88

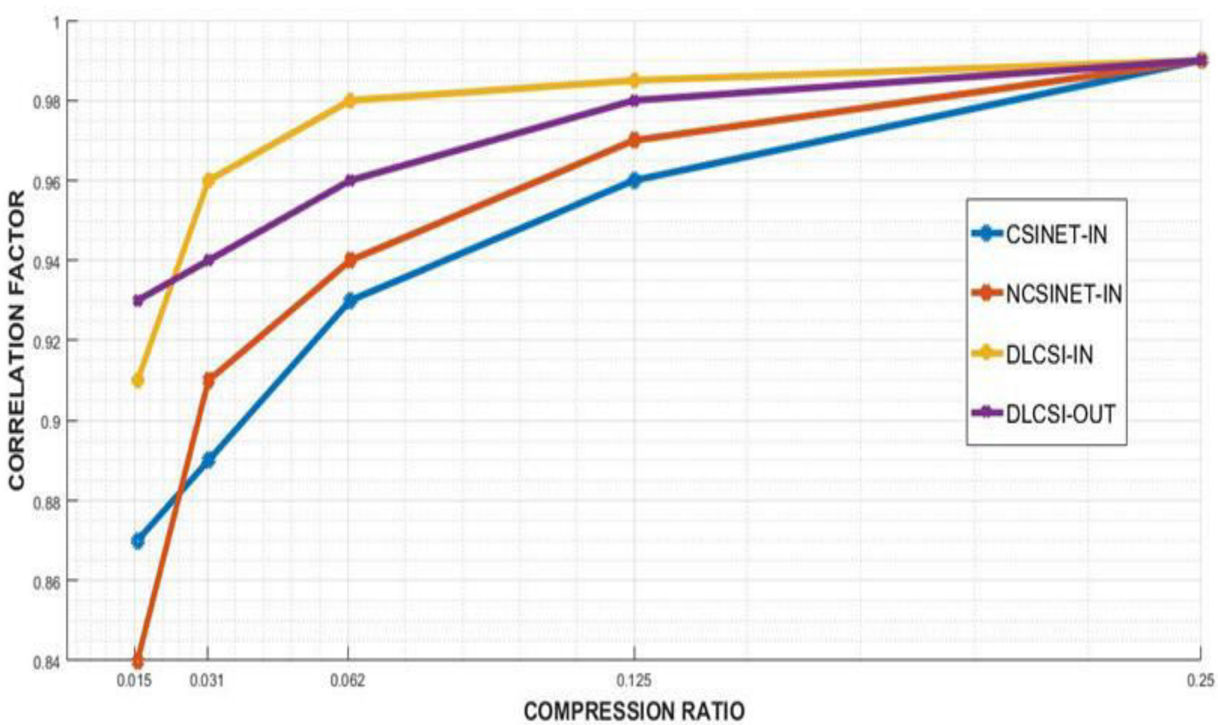

Figure 2correlation factor ρ performance evaluation as a function of compression ratio (γ) using proposed DLCSI model in comparison with state-of-art-techniques

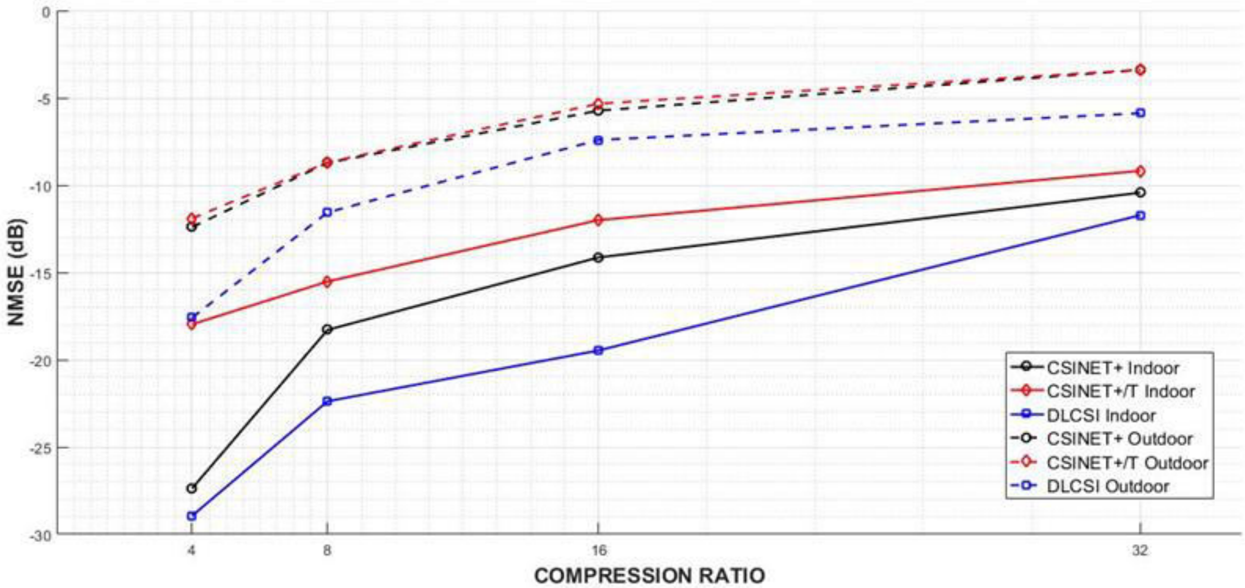

Figure 3 NMSE (dB) performance comparison of proposed DLCSI model with $CsiNet+$ and $CsiNet+/T$for both indoor and outdoor scenarios

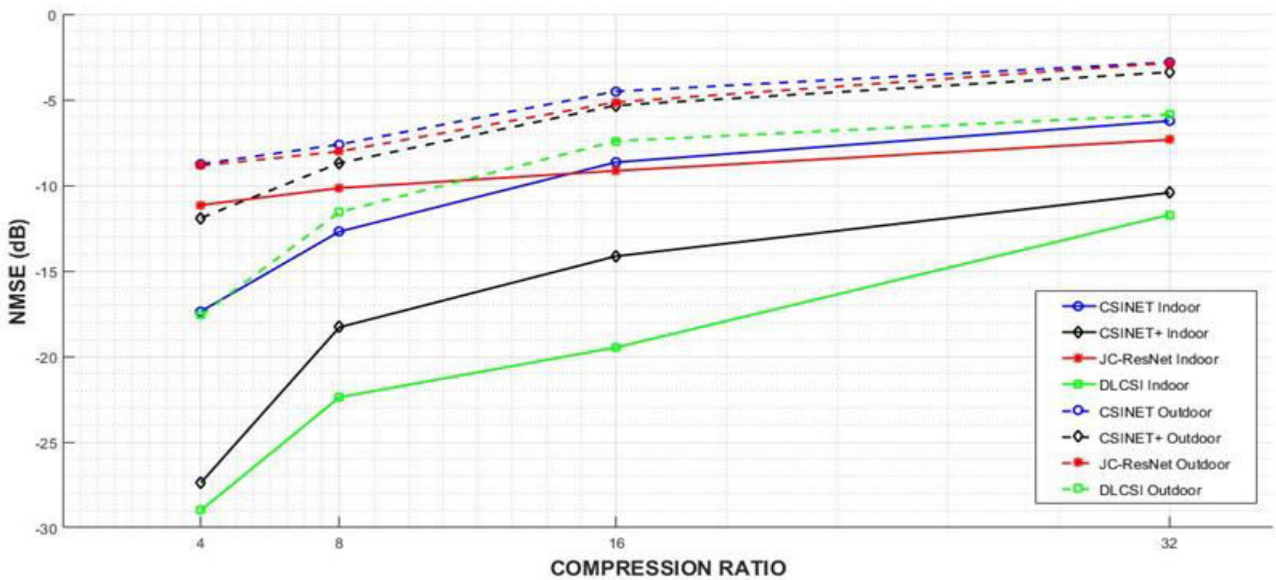

Figure 4NMSE (dB) performance comparison of proposed DLCSI model with $CsiNet+$,$CsiNet$ and JC_ResNet. Proposed DLCSI shows noticeable accuracy advantages under all CRs.

5 Conclusion:

In this article, Deep Learning-based Channel State Information (DLCSI) Model is presented for effectively estimate channel state information and reduce channel overhead. A massive Multiple Input

Multiple Output (MIMO) system is also employed for effective 5G bandwidth spectrum utilization in coordination with cloud technology. The proposed DLCSI model obtain precise CSI at source station by reducing channel overhead and antenna interference. Deep learning methods are utilized to handle absolute and imaginary coefficients which is acquired from the correlation of upstream and downstream CSI components, to study the structures of large datasets and handle their critical processing with high speed.Cloud computing technology is adopted for their exceptional resource pooling capabilities and high storage capacity.A detailed mathematical modelling is presented to evaluate CSI and reduce channel load. The proposed DLCSI model ensure high channel feedback efficiency, high Quality of Service (QoS), channel estimation accuracy. The performance results obtained from COST 2100 MIMO channel model. The performance of proposed DLCSI is compared with various state-of-art- CSI estimation techniques as well as various state-of-art CSI methods based on multiple performance matrices such as Normalized Mean Square Error, CSI accuracy and correlation factor as a function of compression ratio using indoor and outdoor CSI matrices. A detailed quantitative and qualitative analysis of simulation results are presented to represent CSI estimation evaluation. The proposed DLCSI model outperforms all the state-of-art-CSI estimationtechniques for both indoor and outdoor scenarios.

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