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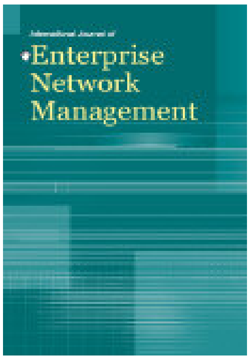

International Journal of Enterprise Network Management

ISSN online: 1748-1260 - ISSN print: 1748-1252
https://www.inderscience.com/ijenm

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DOI: 10.1504/IJENM.2024.10055936

Article History:

Received:	29 April 2022
Accepted:	20 October 2022
Published online:	19 March 2024

Edge controller-based deep learning framework for data-driven view in 5G cellular network

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Abstract: The emergence of the 5G portable network has brought plenty of advantages. Notwithstanding, it provoked new difficulties in the 5G organisation's online protection guard framework, resource management, energy, and reserve, along these lines making the current methodologies out of date to handle the new difficulties. This paper brings an effective edge-based DL model for a 5G cellular network. It gives insights about cloud controller managing RAN for transferring data from user devices to the core network, for example, network strength, security capacities, and network versatility. The proposed engineering comprises four unique layers recognised as network orchestration layer, RAN controllers layer, distributed units layer, and service layer. It uses a DCNN-based model and also further converges with feed-forward organisations to learn the effect of organisation designs and other outside factors. To enhance the safety features of the proposed model, we have used AES methods besides DCNN on the edge. Experimental studies state that while evaluating our DL incorporated model with other techniques, the proposed model outperforms under measures like accuracy, memory utilisation, sensitivity, etc.

Keywords: edge; 5G; cellular network; deep learning; DL; controller.

Reference to this paper should be made as follows: Shamsudheen, S., Anoop, A., Appukuttan, A. and Gopinathan, P. (2024) 'Edge controller-based deep learning framework for data-driven view in 5G cellular network', *Int. J. Enterprise Network Management*, Vol. 15, No. 1, pp.93–108.

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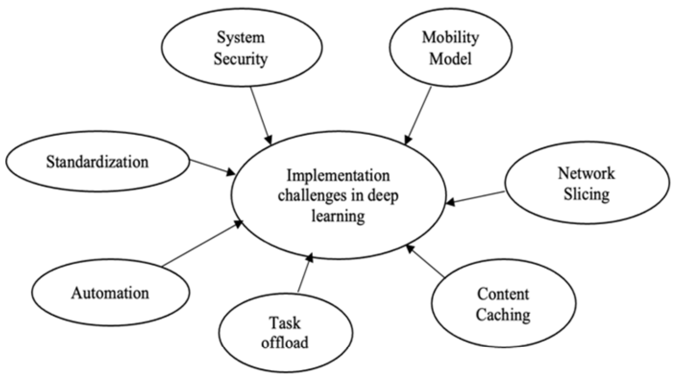
1 Introduction

By 2024, 5G portable edge registering is expected to be a multi-million-dollar industry with big business organisations, arriving at USD 73M. Every year, the complexity of information keeps on developing. The ascent of organisation intricacy frameworks originates from the increment of on-request and adjustable administrations. Web access suppliers should oblige traffic for web perusing, associated vehicles, video web-based, internet gaming, voice over IP, and consistently on internet of things (IoT) gadget transmissions. New imperatives presented by on-request benefits as recorded above require an extreme change of fixed and portable access organisations. Fifth-generation (5G) portable organisations are being created to serve the rising degrees of traffic request and variety. To adapt to the complex traffic requested by present-day clients, network administrators are taking on distributed computing methods. 5G providers will utilise software Define networks (SDN) and network function virtualisation (NFV) to reduce the functional expense of developing versatile organisations to give on-request benefits (Cheng et al., 2021). In the long run, and clients can expect execution upgrades because5G is improved to give low-idleness, high-accessibility, and high-data transmission correspondence for quite some cases, including delay-touchy applications like independent vehicles and mechanised Industry 4.0 robotic technology.

Mobile edge computing can supplement the objectives of the entrance organisation to settle existing difficulties, including the nature of administration/experience, security, and power utilisation as a feature of the important organisational change (Trakadas et al., 2021). Close to NFV and SDN, portable edge registering was perceived by the European 5G public-private partnership (PPP) as a key to empowering innovation that will assist in the fulfilling of requesting necessities for throughput, dormancy, versatility, and mechanisation in 5G (McClellan et al., 2020). Portable edge figuring places computational handling power nearer to the end client. This closeness reduces how much traffic is conveyed across the centre organisation to huge server farms, further developing reaction speed with latencies under ten milliseconds (Wang et al., 2020), and arranges with server farms to offload a few computational undertakings like a web-based derivation from the fundamental cloud. Versatile edge registering can empower ongoing investigation through distributed computing capacities in a safe and setting mindful way with a coordinated effort between network administrators and application suppliers (McClellan et al., 2020).

Figure 1 major implementation challenges of dl



Overseeing a huge number of heterogeneous associations under severe reaction requirements for applications, administration creation, and organisation presents a perplexing test to 5G organisations utilising versatile edge registering. To understand the benefits of portable edge figuring, there is a need to foster a computerised methodology to give, arrange, and oversee network administrations and applications under conditions that change over the long run and across regions. A promising arrangement is presented to AI (ML) to organise activities to meet this new arrangement of requests that are past the restrictions of conventional enhancement procedures (Mao et al., 2018). The advancement of the 5G centre organisation and versatile edge figuring division of work relies upon a mechanised network board that is fuelled by efficient AI (ML) strategies. Customary improvement procedures are not adequately versatile to deal with the intricate, constant examination expected in 5G organisations. In the next 20 years, AI will become commonly known for design acknowledgment. A subset of ML, deep learning (DL), has been broadly investigated and applied inside the fields of online vision (Yu et al., 2020) and regular language handling (Gumaei et al., 2021). 5G organisations can be upgraded to naturally configure, streamline, secure, and recuperate utilising the intellectual ability of DL, although this strategy likewise presents open issues regarding progressive reaction, energy utilisation, and advancement of OPEX and CAPEX. Combining cloud-based innovations and computerisation with DL in versatile edge figuring will increase asset utilisation and efficiency, increment strength, advance power utilisation, increment incomes, and give simplicity of activity to specialist organisations (Koubaa et al., 2020). Figure 1 depicts the major implementation challenges of DL. In this paper we propose the new model to address the limitations like frequency reuse, resource allocation, behaviour of networks and cost savings.

1.1 Key highlights

1. We have proposed a secure and effective conceptual framework for data drive view in a 5G network that combines DL technologies.
2. DL is used on the edge.
3. AES algorithm is used to enhance the security levels of the proposed framework.
4. Evaluated the proposed DCNN with various performance measures and compared it with other cutting-edge methods.

2 Related works

Polese et al. (2020) designed a data-driven architecture for cellular networks with the applications of machine learning. They have evaluated its performance with real data which was obtained from the major US network operators. In that regard, they have provided insights on how to dynamically cluster and associate base stations and controllers, according to the global mobility patterns of the users. Also, they have described how the controllers can be used to run ML algorithms to predict the number of users in each base station, and a use case in which these predictions are exploited by a higher-layer application to route vehicular traffic according to network Key Performance Indicators (KPIs). They depict that the prediction accuracy improves when run on machine learning algorithms that rely on the controllers' view and, consequently, on the spatial correlation introduced by the user mobility, concerning when the prediction is based only on the local data of each single base station (Liang et al., 2019).

Wang et al. (2020) surveyed the convergence of edge computing and DL. They reviewed and discussed in their paper, the application and scenario of edge computing and DL, the practical implementation methods, and enabling technologies, i.e., DL training and inference in the customised edge computing framework, and the challenges and futuristic scopes of more pervasive and fine-grained intelligence. They demand that by consolidating information scattered across the communication, networking, and DL areas, their survey can help readers to understand the connections between enabling technologies while promoting further discussions on the fusion of edge intelligence and intelligent edge, i.e., edge DL.

McClellan et al. (2020) evaluated the opportunities and applications of DL in 5G networks. In their work, they discussed the state of the art for ML within mobile edge computing and the advances needed in automating adaptive resource allocation, mobility modelling, security, and energy efficiency for 5G networks. They showed that MEC is the most desirable candidate for the new verticals, features, and service categories required to establish 5G. They provide a detailed key concept of DL and how it can be implemented to act best in MEC environments with computational memory limitations. Table 1 depicts the summary of state-of-art works.

Gumaei et al. (2021) introduced a 5G enabled drone identification and flight mode detection mechanism with the integration of blockchain and deep recurrent neural network. In their work, raw RF signals of different drones under several flight modes are remotely sensed and collected on a cloud server to train a deep recurrent neural network model and then distribute the trained model on edge devices for detecting drones and their flight modes. The integrity of data and data transmission security is done in the proposed framework by blockchain. Their proposed model's performance was measured based on a public dataset, namely DroneRF, and it attained greater accuracy.

Table 1 State-of-art works (see online version for colours)

DL method	*Remarks*
DNN	The spatial temporal relationships between stations to predict future demands
DNN	Used to identify real-time traffic
DNN	To identify real time traffic and assign network slice
DNN	It decreases computational time and energy consumption
RNN	Using predictive handover can reduce signaling overhead, latency, cell dropping, and radio resource waste.
RNN	It anticipates user movement and service types to cache and offload tasks
RL	Using caching and computation for vehicular networks both at same time
RL	Uses the scheduling of offloaded tasks in vehicular networks
RL	Uses MEC security policies in order to protect against unknown attacks

Rathore et al. (2021) proposed a 5G enabled IoT system with the integration of DL in which security features were enhanced by the blockchain. In their system, the DL and blockchain operations emerged from four system layers, namely cloud, fog, edge, and user layers. They measured the performance of the proposed system with various measures such as latency, accuracy, and security and its validity in futuristic and practical applications.

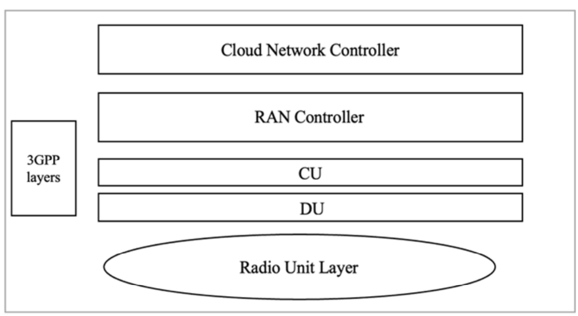
Chergui and Verikoukis (2019) proposed a 5G network that is reliable and possible end-to-end slicing dynamically with the application of offline SLA constrained DL. The various slices' tenants (i.e., logical operators) are progressively allocated secluded bits of physical resource blocks (PRBs), baseband handling assets, backhaul limit as well as data forwarding elements (DFE), and SDN regulator associations. By conjuring enormous KPIs datasets originating from a live cell network supplied with traffic tests, they have presented a low-intricacy slices' traffic predictor based on a soft gated recurrent unit (GRU). They then, at that point, worked at each virtual organisation and trained them to appraise the necessary assets in light of the traffic per cut, while not abusing two assistance level arrangements. In particular, infringement rate-based SLA and asset limits-based SLA. This was accomplished by incorporating dataset-subordinate summed-up non-arched imperatives into the DNN disconnected enhancement assignments that were settled using a non-lose two-player game technique. In this regard, they feature the job of the fundamental hyperparameters in the compromise among over-provisioning and slices' isolation. Further, utilising the unwavering quality hypothesis, they gave a shut structure investigation to the lower bound of the alleged dependable assembly likelihood and featured the impact of the infringement rate on it. In Navya and Deepalakshmi (2019), authors employ a combination of machine learning algorithms namely extreme learning machine algorithm with k-means clustering and analytic hierarchy process, for the prediction

In Jeyaraj and Sankar (2019), energy parameters are calculated and data are routed to the coordinator node for further communication. An efficient node is selected based on the least cost value that depends on high residual energy and less distance to sink.

3 System architecture

In our work, we present the new design paradigms for the 5G RAN to make it possible to practically deploy intelligence in cellular networks so that it can overcome the limitations and constraints of 4G LTE deployments. Figure 2 depicts the proposed system architecture. The different layers of controllers in our architecture are used to aggregate and process network data using DL techniques. This is done with a multi-layer semi-distributed point of view that strikes a balance between the decentralised 4G approach and a completely centralised approach that would be impractical due to the amount of data to be processed. It should be noted that the proposed architecture only applies to the control plane and has no bearing on data packet routing. In this case, DL is on the cutting edge of architecture. In addition, we have implemented an AES algorithm to eliminate security threats to a higher level.

Figure 2 System architecture



The proposed system architecture has four layers namely,

1 Network orchestration layer: In this layer, services are done. It consists of CU association and control loop on a sec/min timescale.

2 RAN controller layer: It is deployed at the edge and of the control loop on a 10–100 ms timescale. It orchestrates CUs/DUs and runs DL algorithms.

3 Distributed units: It is used at the edge with 3G PP high layers and controls loop on an ms timescale.

4 Radio units layer (RUs): It is used in the field with RF equipment, and the lower layers of the 3G PP stack and control loop are on a sub-ms timescale.

4 Integration with 3G PP networks

The proposed architecture exploits a multi-layer overlay that is compliant with 3G PP NR networks. The overlay consists of three main elements which are discussed below.

4.1 RAN

It is deployed to provide cellular service to the users and includes the 3G PP NR CUs, DUs, and RUs. The RAN handles the data plane of the users, i.e., the user traffic is forwarded from or to the core network and the public internet from the CUs.

4.2 RAN controllers

This controls and coordinates the RAN elements. Each RAN controller is associated with a cluster of gNBs and is deployed in MEC, to minimise the communication latency with the RAN. Some of the control-plane processes are assigned to the RAN controllers, which can benefit from the cluster-based overview. RAN controllers can manage UE-level connectivity, by coordinating handover decisions and performing load balancing, or can enforce quality of service (QoS) policies. Moreover, the RAN controllers can be deployed in the same edge data centres that host the CU for a certain area, to minimise the CU-controller latency and to guarantee interconnectivity across the different controller domains, following the trends for cloud and edge-based deployment of 5G networks. RAN architectures enable operators to provide network self-optimisation capabilities, which use automation to manage a network more efficiently.

4.3 Cloud network controller

The cloud network controller, which orchestrates the RAN controllers and provides application-layer services, can be deployed in a remote cloud facility.

A multi-layer controller architecture combines the benefits of the scalability of a distributed approach with the performance gain given by a partially-centralised view of the network. Each layer implements control functionalities with different latency constraints, allowing the network to scale: the DUs schedule over-the-air transmissions on a sub-ms basis, the RAN controllers may decide upon users' association on a timescale of tens of milliseconds, and, finally, the cloud network controller can operate on multiple second (or even longer) intervals, for example, to update the association between gNBs and RAN controllers. At each additional layer, it is possible to support a larger number of devices (e.g., a DU controls tens of UEs at most, while the RAN controller can be designed to handle hundreds of UEs), and, given the more relaxed constraints on the decision timescale, it is possible to implement more refined and complex decision policies, based on DL algorithms enabled by the larger amount of data given by the clustered and/or centralised views.

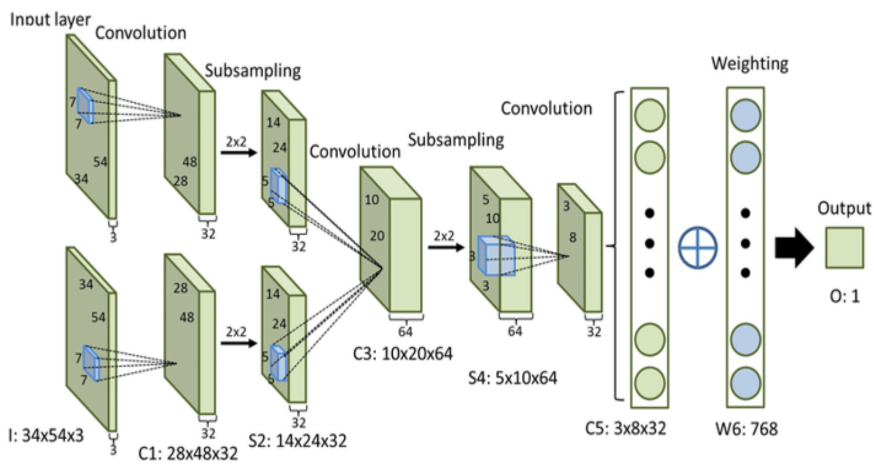
5 Deep learning edge

In our DL edge, we have used well known DL method, namely deep convoluted neural network (DCNN). Figure 3 depicts the architecture of DCNN.

The input will be fed to this model, in which the maximum pooling layer performs down-testing by isolating the contribution to rectangular pooling districts and processing the greatest estimation of every locale. At the end of the day, these pooling layers lessen the number of boundaries to be learned, and consequently, forestall overfitting. Then, a solitary worth is returned for each info ultrasound picture as the yield. All through the preparation, a forward and reverse pass through the organisation is acted in every cycle. In the forward pass, each layer applies its enactment capacity to the yields of the past layer to produce new yields. Assume that a layer takes L1, …, Ln as contributions from past layers and creates the yields O1, …, Om for the following layers. At that point, the misfortune work Lf between the genuine targets T and the expectations Y is determined toward the finish of the forward pass. During the retrogressive pass, each layer registers the subordinates of the misfortune L regarding its sources of info and loads, utilising the subsidiaries of the misfortune as for the yields of that layer. To figure out the subordinates of the misfortune, the chain rule can be utilised:

$$\begin{aligned} &\frac{\partial L}{\partial X^{(1)}} = \sum_j \frac{\partial L}{\partial Z_j}\frac{\partial Z_j}{\partial X^{(0)}} i = 1,\ldots, number\ of\ inputs\ and\ j = 1,\ldots, number\ of\ outputs \\ &\frac{\partial L}{\partial W_i} = \sum_j \frac{\partial L}{\partial Z_j}\frac{\partial Z_j}{\partial W_i} i = 1,\ldots, number\ of\ learnable\ parameters\ and \\ &\quad j = 1,\ldots, number\ of\ outputs \end{aligned} \tag{1}$$

Figure 3 Architecture of DCNN (see online version for colours)



Gaussian distribution for the weights that are initially made will have a mean value of 0 and with standard deviation (SD) of 0.01. We have utilised Adam (got from adaptive moment assessment) (She et al., 2021) calculation to refresh the organisation boundaries (loads and inclinations) and limit the loss function. The gradient descent calculation utilises a solitary learning rate for every one of the boundaries. While advancement calculation improves network preparation by utilising learning rates that consequently adjust to the loss function being upgraded. It utilises an additional energy term and a component-wise moving normal technique:

$$f_j = \beta_1 f_{j-1} + (1-\beta_1)\nabla E(\theta_j) q_2 = \beta_2 q_{j-1} + (1-\beta_2)\left[\nabla E(\theta_j)\right]^2 \tag{2}$$

The rectified linear unit (ReLU) layer has been utilised as an enactment work in convolutional profound neural organisations. It plays out an edge procedure on every component of the information, where any worth under zero is set to nothing. Likewise, a bunch of standardisation layer has been utilised to standardise the contribution of each layer across a small-scale group and accelerate preparation while at the same time diminishing the affected value to organise instatement. 0.0001 was chosen for the learning rate through experimentation. Convolutional neural organisations figure out how to recognise highlights like tone and edges in the first convolutional layers (Shafin et al., 2020).

5.1 AES edge

While emerging, the proposed framework may contain certain intrusion-related problems. To improve the security standards of our proposed system, we used an AES model at the edge in conjunction with a DL model. The National Institute of Standards and Technology (NIST) published the advanced encryption standard (AES) (Gacanin and Renzo, 2020) in 2001. AES is a symmetric block cipher that uses a single key for both encryption and decryption. The AES algorithm's input and output are both sequences of 128 bits. This algorithm employs a key of 128, 192, or 256 bits. AES is based on 8-bit bytes. Using the polynomial representation, these bytes are interpreted as infinite field elements:

$$f(x) = b_{n-1}x^{n-1} + b_{n-2}x^{n-2} + \ldots + b_1 x + b_0 = \sum_{i=0}^{n-1} j b_1 x^i \tag{3}$$

where each b_i has the value of 0 or 1.

The AES 128-bit input block is arranged in a 4x4 state matrix, as shown in Figure 1. The matrix elements are denoted by the variable b_{ij}, and *i, j* are the row and column numbers, respectively. AES allows for rounds based on the size of the bits in key variables. For our experiment, 256-bit key size is used and thus the no of rounds used is 14 rounds, denoted by Nr. The key scheduling algorithm is used in AES to provide keys to each round. The key scheduling algorithm is designed in such a way that revealing any round key returns the original input key from which the round key was derived.

5.2 SubBytes

In the AES, Tis is a nonlinear step. It employs an S-box on the bytes of the state matrix. Each byte of the state matrix is replaced by its multiplicative inverse, which is then fine-mapped as follows:

$$b_i' = b_i \oplus b_{(i+4)mod8} \oplus b_{(i+5)_{mod8}} \oplus b_{(i+6)mod8} b_{(i+7)mod8} \oplus c_i, for\ 0 \le i < 8 \tag{4}$$

where the byte's i^{th} bit is denoted by b_i and c_i is the byte's c i^{th} bit has the value of01100011.So the relationship between the input byte x and the S-box output y is $y = A.x{-}1$ + B, and constant matrices (Bonati et al., 2021) are represented by A and B.

- Shift rows: The last three rows of the state matrix were rotated by a particular no of byte positions. It is carried out as:

$$s'_{u,c} = s_{(u,(c+t(u+kb))modkb)}\ for\ 0 < u < 4\ and\ 0 < c < kb \tag{5}$$

kb denotes the state matrix's no. of words (each column will be taken as a word). In AES, kb will be 4, as the input size is 128 bits and the state matrix is 4 × 4. The state matrix's cell is represented by the letter s, followed by the index of row *r* and column *c*.

Polynomials over GF (2^8) and multiplied modulo x^{4+1} with a fixed polynomial (x), given by

$$a(x) = \{03\}x^3 + \{01\}x^2 + \{01\}x^1 + \{02\} \tag{6}$$

columns of state matrix is calculated by

$$s'(x) = a(x) \otimes s(x)$$

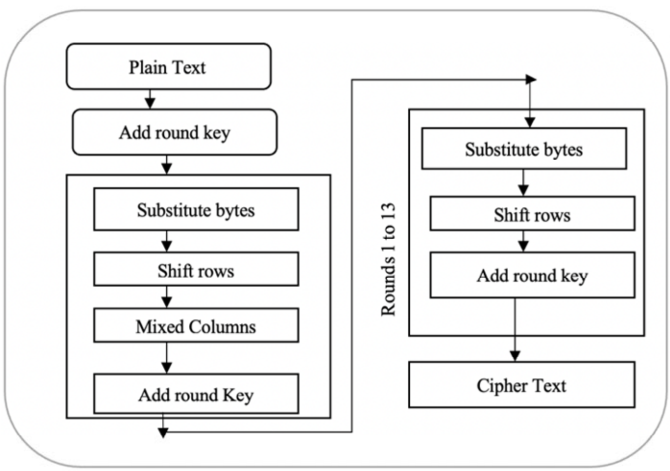
Here the state matrix's state is $s(x)$.

Add round key: a simple bitwise XOR operation is needed to combine a round key with a state. The size of each round key is specified in the key schedule as kb words. To meet the following requirement, each of the kb words is added to the state matrix's columns:

$$[s'_{0,c}, s'_{1,c}, s'_{2,c}, s'_{3,c}] - [s_{0,c}, s_{1,c}, s_{2,c}, s_{3,c}] \oplus [w_{round} \times_{kb+c}]], \textit{for } 0 \le c < kb \tag{7}$$

where bitwise XOR is represented by ⊕ and the round number at which the round key is added is called round and $0 \le round < kr$. Except for the final round, all of these steps are repeated for each round of the AES. The mix column step is skipped in the final round. Figure 4 depicts the round function process for a 14-round AES.

Figure 4 Round function steps in 14-round AES



The addition of round keys, which are generated by the key expansion routine, is an important part of the round function stages. The key expansion produces Md(Ms + 1) words in total: the algorithm requires an initial set of Md words, and each of the Ms rounds requires Mb words of key data. The key schedule that results is a linear array of 4-byte words denoted by [wi], 0 Md(Ns + 1). Rotword () is another function that is used to perform a circular permutation. In linear permutation we have to consider the position of data values, whereas in circular permutation there is not any need for start or end. *Rcon*[*i*] is around constant array containing values specified as [*xi*–1, 00, 00, 00] with *xi*–1 powers of *x* in the array.

$$Rcon[i] = x^{(i-4)}\ /^{4}\ mod\left(x^{8} + x^{4} + x^{3} + x + 1\right), where\, i\, is\, the\, current\, round \tag{8}$$

6 Performance analysis

We have analysed our proposed model with various parameters such as accuracy, sensitivity, specificity, computational time, recall, F1-score, TPR, and FPR. Predictions that are positive and correct are called true positives (TP). Predictions that are negative and correct are called true negative (TN). Predictions that are positive and false are called false positives (FP). Predictions that are negative and false are called false negatives (FN). Table 2 depicts the matrices of performance.

Table 3 depicts the comparison of models with sensitivity, specificity, and accuracy; Figure 5 depicts the analysis of Models with parameters such as sensitivity, specificity, and accuracy of various network datasets and average values. Table 4 depicts the comparison of models with recall, f-score, and memory utilisation, and Figure 6 depicts respective graphs.

Table 2 Metrics of performance measures (see online version for colours)

Performance measures		*Mathematical equations*
1	Sensitivity, TPR	*TP1/(TP1+FN1)*
2	Specificity, S	*TN1/(TN1+FP1)*
3	Precision	*TP1/(TP1+FP1)*
4	Accuracy	*(TP1+TN1)/(TP1+FN1+TP1+TN1)*
5	F Score	*2*TP1 / 2TP1+FP1+FN1)*

Table 3 Comparison of models with sensitivity, specificity and accuracy

Dataset	*Models*	*Sensitivity (%)*	*Specificity (%)*	*Accuracy (%)*
1	VGG16	88	78	85.9
	DENSENET169	87.3	84	87.4
	CNN	89.6	88	90.3
	LSTM	90.67	81	93.1
	DCNN(Ours)	91.2	89	94.4
2	VGG16	83.9	82	80
	DENSENET169	79.5	85	86.2
	CNN	83	88.9	82.8
	LSTM	85	80.3	87
	DCNN(Ours)	84	85	95
3	VGG16	83.6	81	82.9
	DENSENET169	82.9	84.5	86.5
	CNN	86.6	86.3	84.5
	LSTM	87.8	83.9	89.7
	DCNN(Ours)	88.4	88.3	94

Table 3 Comparison of models with sensitivity, specificity and accuracy (continued)

Dataset	*Models*	*Sensitivity (%)*	*Specificity (%)*	*Accuracy (%)*
4	VGG16	87	77	84.8
	DENSENET169	86.2	83	86.3
	CNN	88.5	87	89.2
	LSTM	89.56	80	92.01
	DCNN(Ours)	90.1	88	93.3
5	VGG16	89	79	86.1
	DENSENET169	88.4	85	88.5
	CNN	90.7	89	91.4
	LSTM	91.77	82	94.2
	DCNN(Ours)	92.3	90	95.55

Figure 5 Analysis of models with parameters such as sensitivity, specificity, and accuracy of various datasets and average value (see online version for colours)

Table 4 Comparison of models with recall, f-score, and memory utilisation

Dataset	*Models*	*Recall (%)*	*F-score (%)*	*Memory utilisation (%)*
1	VGG16	82	83.7	90
	DENSENET169	84.1	87	92
	CNN	86.6	86	94
	LSTM	88	79	89
	DCNN(Ours)	91	85	88
2	VGG16	83	84.8	91
	DENSENET169	85.2	88	93
	CNN	87.3	87.1	95
	LSTM	89	80	90
	DCNN(Ours)	92	86	89
3	VGG16	84	85.9	92
	DENSENET169	86.3	89	94
	CNN	88.4	88.2	96
	LSTM	90	81	91
	DCNN(Ours)	93	87	90
4	VGG16	82.10	83.	92.01
	DENSENET169	84.2	87.13	92.25
	CNN	86.7	86.12	94.02
	LSTM	88.1	79.1	89.02
	DCNN(Ours)	91.1	85.08	91.11
5	VGG16	84.02	86.12	92.20
	DENSENET169	86.5	89.25	94.02
	CNN	88.6	88.5	96.6
	LSTM	90.04	81.2	91.01
	DCNN(Ours)	93.5	87.20	90.02

Figure 6 Analysis of models with parameters such as recall, f-score, and memory utilisation of various datasets and average value (see online version for colours)

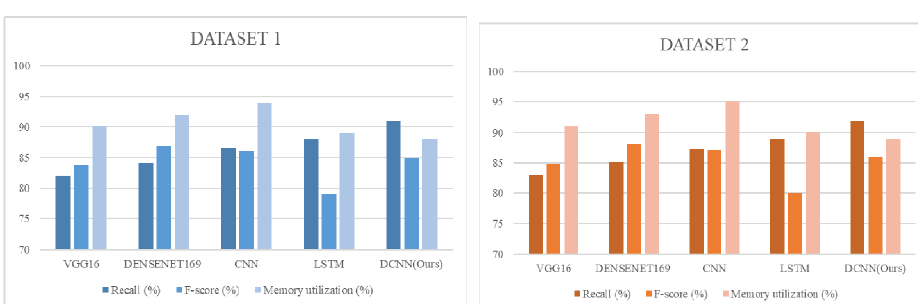
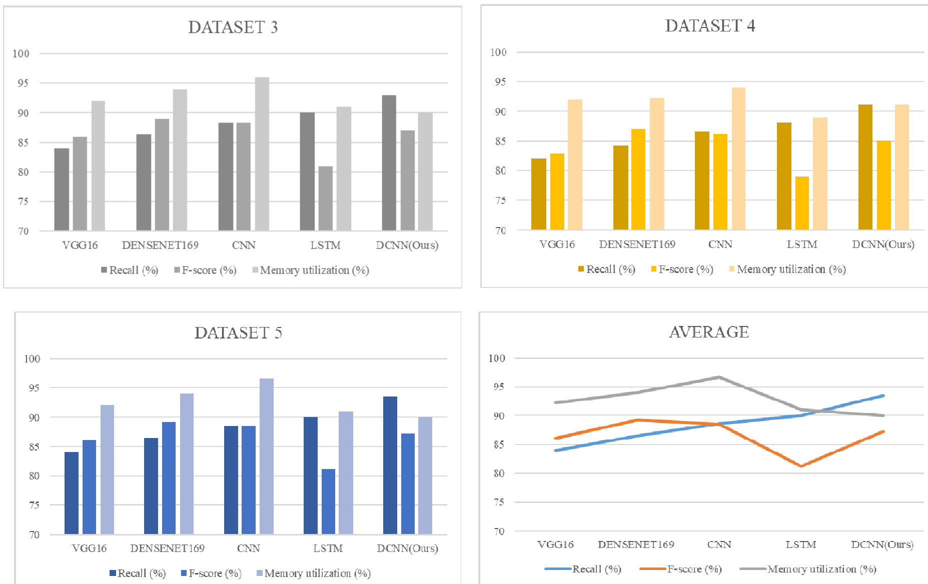


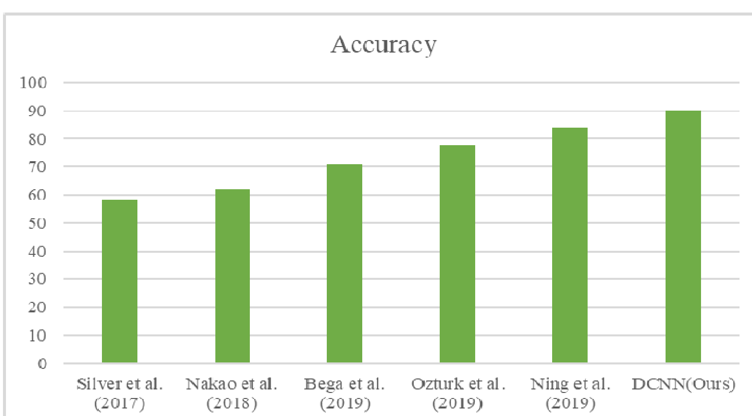
Figure 6 Analysis of models with parameters such as recall, f-score, and memory utilisation of various datasets and average value (continued) (see online version for colours)



The analysis shows the variations in different datasets and how the accuracy, sensitivity and specificity of models affect the memory utilisation. From the above graphs, it is obvious that the proposed DCNN methods outperform well than other methods. Its higher accuracy and sensitivity help in the efficient handling of 5G networks.

Our proposed model has lower memory utilisation. This reduces the storage and increases the speed of the system. Figure 7 depicts a comparative study of the proposed model with other latest models.

Figure 7 Comparison of models (see online version for colours)



7 Conclusions

The emergence of 4G has improved connectivity much better than that of 3G. So, the arrival of the 5G network can revolutionise the field of telecommunication and some other related areas. Edge controller-based DL framework for data drive view in 5 G cellular networks. The proposed architecture consists of four important layers namely network orchestration layer, RAN controllers layer, distributed units layer and RUs layer. The edge of the system consists of a DL algorithm namely DCNN which enhances the performance of the architecture. The transmission of 5G networks may possess certain security threats. To avoid those, we have used an AES algorithm. We have evaluated our model with various measures and compared it with other cut edge models. Our model outperformed well with an average accuracy of 95%.It helps in the enhancement of present systems and the creation of new ones. It will pave the way which leads to creating the 6th generation (6G) in the future. There are a lot of implementation challenges in the case of DL at 5G edge which include security issues, high data usage, and raised data cost. We can use different prediction algorithms in real-time scenarios like cellular network to improve accuracy and consider parameters like handover, energy consumption and throughput.

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Abbreviations

5G	Fifth-generation
MEC	Mobile edge computing
CAPEX	Capital expenditure
AES	Advanced encryption standard
3GPP	Third generation partnership project
DCNN	Deep convoluted neural network
SDN	Software-defined networks.