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# Deep Inception-based Siamese Network for Active User Detection in Grant-free NOMA System

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***Abstract*— Recent years have seen a rapid growth and development in the field of wireless communication networks. Specifically, the grant-free access and non-orthogonal multiple access (NOMA) in connection with deep learning algorithms. Which facilitate massive machine-type communication devices and improve performance in terms of active user detection (AUD). The detection procedure in the grant-free NOMA systems is difficult due to the signal being received is superimposed. Existing studies focused on deep learning methods to increase the detection performance. However, the models show limitations over the computational complexity. Integration of LSTM and GRUs can only handle temporal modeling not the spatial correlations. The aim of this paper is to add inception modules with Siamese network. The proposed S-net goes wider instead of deeper which reduces computational complexity and increase detection performance Furthermore, parameter sharing characteristics of S-Net helps in generalizing the performance for large sparse matrices with varying SNR values. The comparative analysis show that the proposed S-Net outperforms existing state-of-the-art methods in an effective manner.**
***Keywords—grant-free NOMA, Active User detection, Siamese network, inception modulus***

## I. INTRODUCTION

NOMA is a term describing the use of multiple access technique that utilize the bandwidth effectively in the fifth generation (5G) wireless communication networks [1]. Due to non-orthogonality mechanism, the received signal is represented as a superimposed information signal with inter-user interference (IUI) of multiple devices in a cell. In order to reduce IUI, device specific non-orthogonal sequence is used by NOMA, and intentionally design non-linear receiver based on successive interference cancellation (SIC) and message pass algorithm (MPA) [2]. In addition to that when NOMA is used with grant-free mechanism, that is GF-NOMA, it supports the massive connectivity to base station for massive machine-type communication (mMTC) devices (for instance, sensors, drones, robots and machines). The primary goal of mMTC is to establish connection among MTC devices and to keep massive connectivity in an uplink dominated network [3]. It has gained lots of attention due to its applications in wireless networks based on machine learning approach such as auto-driving, smart factories, and IoT to name a few. Massive connectivity is desirable in conventional wireless networks namely, narrow band Internet-of-Things (NB-IoT) and Long Term Evolution – MTC (LTE-M) due to complex acknowledgement procedure lacked by orthogonal resource assignment to huge MTC devices [4]. Moreover, due to narrowband-width, it is unable to handle the massive access. Therefore, NOMA with grant-free is getting popular for supporting massive access of MTC devices. Grant-free NOMA authorizes transmission of MTC devices excluding acknowledgement mechanism [5].

As each device in the cell transmits data without any scheduling procedure, a process to identify the transmitting device (i.e., active device) in all the potential devices is desired. This procedure of identifying the transmitting device is termed as *active user detection* (AUD) [6], and it is important to carry out the mMTC, afterward, BS cannot ascertain for the device transmitting information signal and the grant-free NOMA has no meaning without the proper use of AUD process [7]. It is constituted from many existing studies that in a cell a few active devices send information. Due to defined fact that the AUD is required to get information of sparse active connections between passive devices, and this is taken as the problem connected to sparse recovery.

Apart from conventional methods of detection, deep learning models are much efficient to achieve higher detection accuracy. The conventional neural network (CNN) model is the genuine classification models. CNN has a lot of accessible data for training section. The CNN model identifies on the base of a particular class in the training sets [8]. On the other hand, the architecture of Siamese network distinguishes irrespective of the listed class [9]. The deep learning models are dense and complex which limit the performance of the model in terms of training time [10-14]. For instance, a convolutional layer can be designed with a kernel size of 3x3, with input and output of 128 channels. In this scenario, each output channel is linked with the input channel and most of these connections are not used, or taken as redundant. Sparse connection can be used in deep network to cop this problem. This computational complexity limits the sparsity handling that is scalability is affected. Integration of long short-term memory (LSTM) with gated recurrent units (GRU) can only handle temporal modeling but lack in spatial correlation [15-17]. Considering the aforementioned facts, inception module is used to address sparse connection. Inception module takes the small kernel size by 1x1, 3x3, and 5x5 [18].

Xin et al [19] employ the MPA and solved AUD problems considering a single measurement vector. Choi et al. [12] submitted a scheme for detection named as compressed-sensing (CS). The active user identified on the bases of the correlation between the signal received and unique sequence of the device. This scheme shows less performance as the system matrix (i.e., sparsity) get increases and high correlation of columns. The listed parameters such as system matrix columns, correlation of columns, under-determined ratio and the number of devices has the direct relationship and increase as any other parameter goes up and system gained more complex computation. Jiang et al. [20] carried out the detection procedure by estimating the message pass algorithm (MPA). Cai et al. [21] used every other complex direction scheme of multipliers for estimation of active device by a one and multi-carrier NOMA system. Wei et al. [22] presented a superposition of reduction to approximate message passing to build the sparsity for active devices and the resultant sparsity is limited by the computational complexity. Fu et al. [23] recommended using a vector machine and sparse Bayesian learning to determine which device is active. In relation with compressed sensing mechanism, as the number of device keep on increasing which results the higher sparsity of the sensing matrix. Therefore, the detection is poor due to high up correlation in a highly sparsed matrix. This attained high computational complexity. [5], [12]. Thus, a framework which can manage the AUD issues when the number of devices increases and sparsity is required. Lately, deep learning frameworks have been widely applied in many applications due to its success rate concerned with the autonomous games, sentiment analysis, time-series data prediction, image grading, and pattern recognition. [24]. On-going research direction has already been started focusing on deep learning models pertaining to communication systems like wireless-scheduling, MIMO detection, direction-of-arrival approximation. Cui et al. [25] Study proposed the mapping among the interference pattern and optimized scheduling in deep learning models. Shahab et al. [26] DNNs are applied focusing on NOMA symbols for encoding and decoding. Gui et al. [26] Study shows the identification and evaluating of channel in grant-free based NOMA by deploying the deep learning based architecture.

Kim et al. [5] submitted DNNs based grant-free NOMA for AUD only. Miao et al. [27] study has been though about the previous data in NOMA system and LSTM network for AUD. Ye et al. [28] presented his work on DeepNOMA, a multi-user detection method based on deep learning for NOMA Systems. This deal with IUI and employ the muti-task learning patterns for AUD, simultaneously. Emir et al. [29] this study uses LSTM to detect multi-user in grant-free NOMA scheme. Authors submit that proposed model on DeepMUD framework performs better than the conventional methods, and achieves better scalabilities. This framework confined the network to estimate the active user and can manage a great deal on sparse scenario and less sparsity as shown in results. In addition to that, the studies such as [21], [5], [28], and [29] emphasized over active user detection section, thus, do not leverage the computational complexity of the network. Despite all these methods, still there is a need to reduce the complexity and increase the accuracy of the system. Thus, this work presents a mechanism of adding inception modules in Siamese network to reduce computational complexity with increasing the accuracy of active user detection in grant-free NOMA systems.

## II. METHODOLOGY

The assumptions and system model parameters for this study are based on [3] and [4], respectively. We have assumed that a single antenna has been used along with $N$ devices to consider the uplink transmission scenario based on GF-NOMA principles. Most of the devices are silent (inactive), while a few of them are active, thus, they need to transfer some information, accordingly. Based on the limited resources, the target is to identify the active users so that the resources could be efficiently utilized in the aforementioned scenario. Since GF-NOMA systems allow the transmission of information without granting permission, therefore, the problem of active user detection is analogous to sparse signal recovery problem. The conventional systems used pilot systems at the base station to detect the active users, for instance, considering the demodulation reference signal in fourth generation communication system or new radio in fifth iteration of the communication systems. Nevertheless, for achieving the task, channel estimation techniques were widely used such as LMMSE estimator [30], [31]. However, in NOMA systems, the signals from various devices are superimposed within the identical resources, therefore, the channel estimation techniques do not work, appropriately. In this regard, this work proposes Siamese Network (S-Net) architecture for detecting active users in GF-NOMA systems. The proposed S-Net for active user detection is depicted in Figure 1. Let us denote the received NOMA signal with $\bar{y}$. The main aim of the proposed S-Net is to identify the active users from the channels using $\bar{y}$. In this regard, the formulation for mapping $\bar{y}$ to $\rho_{aud}$ ($\widehat{\Omega}$) for active user detection and mapping from $\bar{y}$ to $\rho_{ce}$ ($\Omega_{\mathrm{h}}$) for channel estimation is shown in equation 1 and 2, respectively.

$$\widehat{\Omega} = \rho_{aud}(\bar{y}; \Theta_{aud}), \quad (1)$$

$$\Omega_{\mathrm{h}} = \rho_{ce}(\bar{y}, \widehat{\Omega}; \Theta_{ce}) \quad (2)$$

Where the notations $\Theta_{aud}$ and $\Theta_{ce}$ represent the network parameters for the task of active user detection and channel estimation, respectively. The task of S-Net is to learn the aforementioned mapping in order to maximize the success probability of active user detection while minimizing the error associated with channel estimation.

Existing works have mostly used deep neural networks but they need to train two separate networks in order to map the active user detection and channel estimation, which is

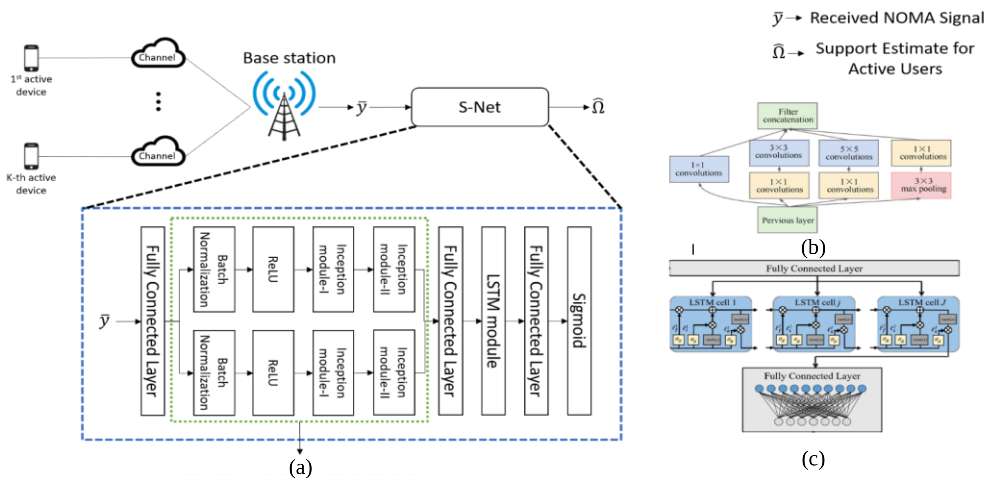



Fig. 1. (a) Siamese Network Architecture. (b) Inception Module I and II [9]. (c) LSTM module and fully connected layer

impractical at times. Therefore, in this regard, the S-Net uses Siamese networks that trains two networks but in a single end-to-end fashion. The twin networks learn the patterns that are associated to both networks and jointly optimized the weights to achieve better performance. Furthermore, existing DNNs takes a lot of training time which is also not sustainable either for the environment or for the task itself. The S-Net employs inception module that not only makes the training faster but also sustainable for the detection task.

Another problem that the S-Net solves is the generalization. Existing networks need to train multiple deep neural networks in order to adapt to the sparsity of active devices, which is also impractical as figure of active devices can exist in magnitudes of hundreds when considering 5G or 6G networks. To cope with this issue, the S-Net employs long short-term memory (LSTM) networks. As depicted in Figure 1, the input to the LSTM networks is characterized by the parameters that are optimized, i.e. $\Theta_{aud}$ and $\Theta_{ce}$. The assumption of S-Net suggests that the LSTM is capable of adapting to the changes to number of active devices, therefore, the sparsity can be handled, accordingly. Additionally, LSTM is also helpful in modeling temporal information while incorporating relevant information such as codewords, and rejecting insignificant information such as the one generated from inactive devices.

Primarily, an LSTM cell is comprised of the two elements. First is the cell state $\ell_c^j$ , and in the second place are three gates, i.e., *forget gate* $\ell_f^j$, *input gate* $\ell_i^j$, and *output gate* $\ell_o^j$ as shown in **Error! Reference source not found.** (c). Input, output, and forget gates make up

the three gates that the call state defines to be the memory to store data removed from preceding inputs throughout subsequent passes along these three gates.

Establishing at each moves, the input $z^j$ and the past output $o^{j-1}$ vectors, the output vector $o^j$ is produced as the information in the cell state is eliminates, writes and read at each gate. In proposed work, the features of active and silent devices are accepted or refused on the bases of input and forget gates, respectively. In addition to the cell state, the memory for storing feature-related data is incrementally changed to gradually improve device identification quality and CE.

Operations at each gate in the $j-th$ LSTM cell is expressed as

$$\ell_f^j = \sigma_g\left(W_f z^j + U_f o^{j-1} + b_f\right), \tag{3}$$

$$\ell_i^j = \sigma_g(W_i z^j + U_i o^{j-1} + b_i), \tag{4}$$

$$\ell_o^j = \sigma_g(W_o z^j + U_o o^{j-1} + b_o), \tag{5}$$

$$\bar{\ell}_c^j = tanh(W_c z^j + U_c o^{j-1} + b_c), \tag{6}$$

$$\ell_c^j = \ell_f^j \otimes \ell_c^{j-1} + \ell_i^j \otimes \bar{\ell}_c^j, \tag{7}$$

$$o^j = \ell_o^j \otimes tanh(\ell_c^j), \tag{8}$$

Where $W_f$, $W_i$, $W_o$, and $W_c$ $\in \mathbb{R}^{\alpha\times\alpha}$ act as the various weights corresponding to $z^j$, and $U_f$, $U_i$, $U_o$, and $U_c$, $\in \mathbb{R}^{\alpha\times\alpha}$ are various the weights corresponding with $o^{j-1}$. Also, $b_f$ , $b_i$ , $b_o$, and $b_c$ $\in \mathbb{R}^{\alpha\times 1}$ act as the various biases, and sigmoid function is $\sigma_g(x) = \frac{1}{1+e^{-x}}$ and hyperbolic tangent function $\tanh(x) = \frac{e^{2x}-1}{e^{2x}+1}$ respectively.

### *A. S-Net Architecture*

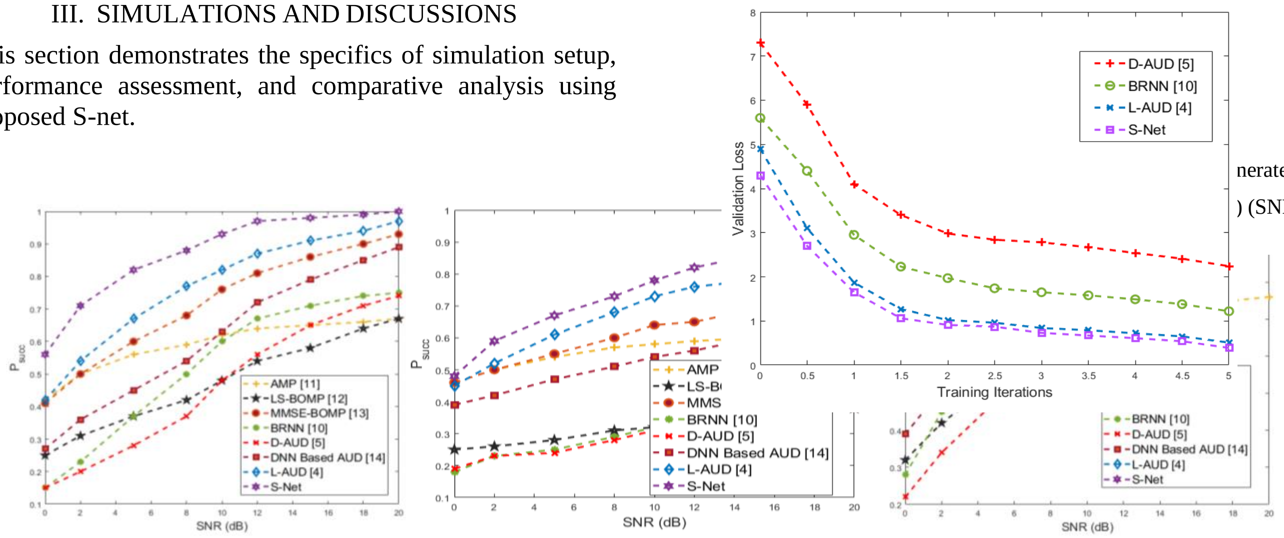
The S-Net architecture is depicted in **Error! Reference source not found.**(a). The architecture first converts the vector $\bar{y}$ to a real vector and then fed to the fully connected layer. The output of the fully connected layer yields a one-dimensional vector, i.e. $\bar{\bar{y}}$ and is formulated according to equation

$$\bar{\bar{y}} = \breve{b} + \breve{W}.\bar{y} \tag{9}$$

Where $\breve{W}$ and $\breve{b}$ are weights and bias, accordingly. The vector $\bar{\bar{y}}$ is then passed through the Siamese network (batch normalization, ReLU, and inception layers) followed by another fully connected layer to generate the probability vector. The probability vector is then provided an input to the LSTM network followed by the decision making layer to classify between active and non-active users. There are two networks that are trained in Siamese fashion, suggesting that both networks have different initialization while all other parameters remain the same. The S-Net uses two optimization functions, the first is binary cross entropy while the second is the sigmoid function.

## III. SIMULATIONS AND DISCUSSIONS

This section demonstrates the specifics of simulation setup, performance assessment, and comparative analysis using proposed S-net.




nerated by arbitrary
) (SNR=10 dB)

(a) (b) (c)

Fig. 2. Probability of success ($P_{SUCC}$) in relation to SNR for multiple K devices .$(a)$ $K = 7$. $(b) K = 10$. $(c) K = 15$.

### A. Simulation Setup

In the simulation, our work focuses on up-link grant-free NOMA systems. Which is taken into account by systems that use orthogonal frequency division multiplexing (OFDM). We set system's bandwidth to have 500 subcarriers. The barrier of 15 kHz is fixed between each subcarrier (as per LTE/NR grade). We placed the quantity of devices to 100 (K=100), with every device transmitting a payload of 250 bits supported by QPSK modulation. In the training phase of S-net for a channel model, we take into account the multipath Rayleigh fading model with tap coefficients. That vary separately for every device in the time domain. We calculate the path loss component $\zeta_i$ taking $\zeta_i = 128.1 + 37.6 log_{10}(\gamma_i)$ [dB], where $\gamma_i$ represents the separation between the BS and $i-$th device. A fixed noise spectral density of -170 dBm/Hz persists. We increase the spreading length of the LDS codeword to $L = 7$, and used an i.i.d Gaussian random variable to generate nonzero values for the LDS codebook.

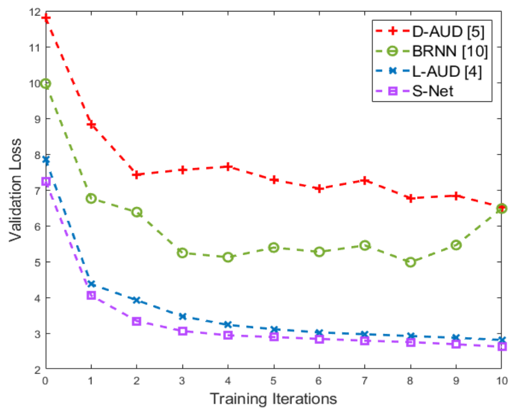
In our simulation for S-net, we fixed $10^7$samples for training, $10^5$ samples for validation, and $10^5$ samples for testing purpose. The training dataset's active device count is drawn at random from the discrete uniform, distribution i.e., K ~ U(1,10). We used the Adam optimizer throughout the training phase, with learning rates of $\eta_A$ =0.0001, and $\eta_C = 0.001$ for AUD and CE, respectively. We set the device activity

Fig. 3 NOMA measurements are generated by K=5 devices (SNR=10 dB)

probability threshold $\tau$, the number of LSTM cells, the number of hidden layers, and the size of the training batch to 0.5,3,256,1000 respectively. As the performance indicator for AUD and CE. We use normalized mean squared error (NMSE), which is calculated as the proportion of the successfully detected active devices, the AUD success probability $P_{succ}$ and normalized MSE of the estimated channels of active device, respectively.

### B. Simulation Results

We measured the performance comparison of s-net in terms of probability of success and validation loss. The probability of success with respect to the function of SNR (signal to noise



ratio) as given in figure 2 for various number of devices. The results show that the s-net outperforms in comparison with the existing studies (such as AMP, LS-BOMP, MMSE-BOMP, BRNN, D-AUD, BRNN, L-AUD etc.).

Additionally, the validation loss as a function of training iterations of s-net as shown in figure 3 and 4. The results show that the s-net has low validation loss to each training iterations, and it keeps on decreasing as the training iteration goes on increasing. Moreover, the comparative analysis shows s-net has less validation loss as existing studies. However, the validation loss for all existing studies are unstable and diverge. And the convergence is not swift due to computational complexity as our proposed work. The probability of detection of existing models is higher for limited SNR and K number of devices. Whereas the proposed work shows a good detection as the SNR and K devices are increases with the existing studies.

TABLE I. S-NET TRAINING TIME COMPARISON FOR VARIOUS SNR LEVELS

| SNR(dB) | 0 | 5 | 10 | 15 | 20 |
|---|---|---|---|---|---|
| L-AUD[4](sec) | $2.94 \times 10^4$ | $3.28 \times 10^4$ | $3.74 \times 10^4$ | $5.42 \times 10^4$ | $7.41 \times 10^4$ |
| S-Net (sec) | $1.37 \times 10^2$ | $1.65 \times 10^2$ | $2.08 \times 10^2$ | $2.77 \times 10^2$ | $3.82 \times 10^2$ |

In

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TABLE I, we report the training time comparison with a recent approach **Error! Bookmark not defined.Error! Reference source not found.** for various SNR levels where runtime is

taken in seconds. The results highlight that proposed S-net reduces the training time by almost a factor of 2 (x/2).

## IV. CONCLUSION

In this paper, we propose a Siamese network architecture S-Net for active user detection in grant-free NOMA systems. We employed two deep network architectures that consist of residual and inception blocks for parallel training to improve the neural expressive power followed by LSTM network to improve the neural expressive power for identification of active user devices. The key idea behind S-Net network architecture is to leverage the parameter sharing characteristics between Siamese network to improve the feature extraction process while generalizing the performance for large sparse matrices. The LSTM is then used to model the temporal characteristics for considering channel estimation for improving the active user detection process. The results demonstrate that the proposed method is effective for arbitrary number of devices with varying SNR values, respectively. Furthermore, the results also reveal that the probability success of the proposed method is higher in comparison to existing state-of-the-art works.

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