Abstract—In this work, we propose two novel deep-learning-based algorithms to solve the wireless channel type (WCT) determination problem. Specifically, the WCT determination problem is recast as a classification problem in deep learning due to their similarities, where a deep neural network (DNN) is trained offline with a diversity of WCTs usually encountered in wireless communications, which is then utilized to perform online WCT determination. In the first algorithm, one WCT is regarded as a single task, while in the second scheme, one WCT is jointly characterized by several independent features, each of which is regarded as a task and is classified respectively by training a DNN in a multi-task-learning manner, and the final WCT is identified by the combination of those channel features. Simulation results show that the proposed algorithms can classify various WCTs instantaneously with high accuracy.

Index Terms—Classification, deep learning, deep neural network (DNN), wireless channel type.

I. INTRODUCTION

In wireless communications, data should be transmitted using a proper modulation and coding scheme (MCS) depending on the channel conditions in order for the receiver (Rx) to be able to decode the data with a target bit error rate (BER) or block error rate (BLER). Which MCS to use is usually determined based on estimated channel state information (CSI) feedback obtained using CSI reference signals (CSIRSs) for the downlink, sounding reference signals (SRSs) for the uplink, or other types of reference signals [1]–[4]. The CSI estimation usually includes channel matrix estimation, signal-to-interference-plus-noise ratio (SINR) estimation and/or mutual information (MI) estimation, as well as MCS estimation. The mapping to MCS from prior estimated parameters, such as SINR and/or MI, usually relies on the wireless channel type (WCT) to ensure that a target BER or BLER can be met. For instance, if the MCS is mapped from the MI, then multiple MI-to-MCS mapping tables [5] are needed for various WCTs, such as additive white Gaussian noise (AWGN) channel, EPA5 (Extended Pedestrian A model with 5 Hz Doppler frequency) with low correlation between Rx antennas, EVA5 (Extended Vehicular A model with 5 Hz Doppler frequency) with high correlation between Rx antennas, among others. More importantly, the mapping table can vary significantly for different WCTs due to their distinct channel properties. Therefore, it is critical to identify the WCT in order to select the correct mapping table. To the authors’ best knowledge, there has been no publicly available solution to WCT determination.

In this work, we propose two novel approaches to WCT recognition leveraging deep learning techniques. Specifically, we recast the WCT determination problem as a classification problem in deep learning, where a deep neural network (DNN) is first trained offline with a diversity of WCTs that are representative in wireless communications, and is then employed to conduct online WCT determination. In particular, in the first approach, one WCT is regarded as one task, which is classified using a DNN trained offline in a single-task learning manner. While in the second algorithm, a WCT is jointly characterized by delay spread/frequency selectivity, correlation between Rx antennas, Doppler spread, and so on, each of which is treated as a task and is classified separately by training a DNN via multi-task learning [6], and the final WCT is determined by the combination of channel features, which is more suitable compared with the first embodiment if the number of WCTs is large.

II. SYSTEM MODEL

We consider a wireless communication link with one next-generation nodeB (gNB) and one user equipment (UE), where the gNB and UE are equipped with $N_G$ and $N_U$ antennas, respectively, where $N_G$, $N_U$ $\geq$ 1. The gNB and UE communicate with each other through a wireless channel, and the transmitted signal is contained in $B$ resource blocks (RBs) and $M$ symbols. At the Rx side (UE for downlink and gNB for uplink), the received signal is first descrambled, which inherently carries channel features and are free from channel estimation errors since they are obtained prior to channel estimation. Therefore, the descrambled signal at the Rx can be employed to assess the WCT.

III. PROPOSED WCT-DETERMINATION ALGORITHMS BASED ON DEEP LEARNING

In this section, we elaborate on the proposed two deep-learning-enabled WCT determination algorithms. In the first algorithm, the WCT determination problem is formulated as a single-task classification problem, where the task is to directly categorize the unknown WCT into one of the types used for training the DNN. In the second algorithm, the original problem is divided into several tasks, each of which represents a feature of the wireless channel to be determined and is classified respectively by training a DNN via multi-task learning, and the final WCT is determined by the combination of those channel characteristics.
A. Single-Task Classification

Without loss of generality, for a given WCT, slot, and signal-to-noise ratio (SNR) combination, the total length of the descrambled signal sequence over all RBs, symbols, and Rx antennas is denoted as $N_{\text{des}}$. The steps for using single-task classification to determine the WCT are detailed in Algorithm 1. Specifically, the descrambled signals in all the RBs, symbols, and Rx antennas used are rearranged into a vector by separating the real and imaginary parts of each descrambled complex signal, putting the real part of all descrambled signals into a vector, putting the imaginary part of all descrambled signals into a vector, and concatenating the two vectors into one. The procedure above is repeated for a wide range of SNR values to eliminate SNR dependency during WCT determination, for a large number of slots to obtain statistically sufficient samples, and for all potential WCTs that are of interest. Afterwards, the training and inference data sets are labeled where one unique label is created for each of the WCTs considered, as demonstrated by Step 12 in Algorithm 1. For example, assuming the WCTs considered are AWGN, EPA5 with low correlation, EPA5 with high correlation, EVAV700 with low correlation, and EVAV700 with high correlation, then the labels for the three delay spread values are [1 0 0 0], [0 1 0 0], and [0 0 1 0], and the labels for the two correlation values are [1 0] and [0 1], and the labels for the three Doppler spread values are [1 0 0], [0 1 0], and [0 0 1]. Finally, the labels for each characteristic are concatenated into an $8 \times 1$ vector to form the overall label for multi-task (three-task in this case) learning using the DNN, e.g., EPA5 with high correlation corresponds to the label [0 1 0 0 0 0], where the first three digits [0 1 0] indicates EPA, the following two digits [0 0] represents high correlation, and the last three digits [0 0 0] denotes 5 Hz Doppler spread. The labels for the other WCTs can be derived similarly. Then the training and inference data sets generated above are employed to train a DNN offline to obtain a trained DNN that can classify an instantaneous WCT online.

Note that as a variant of Algorithm 1, instead of the real and imaginary parts, the magnitude and phase of each descrambled complex signal can be separated, after which the magnitudes of all descrambled signals are put into a vector, the phases of all descrambled signals are put into a vector, and the two vectors are concatenated into one.

B. Multi-Task Classification

The detailed steps for multi-task classification are provided in Algorithm 2, where the method for generating the training and inference data sets is the same as Steps 1-11 in Algorithm 1. The key discrepancy between single-task and multi-task classifications lies in how the training and inference data sets are labeled. As pointed out previously, a WCT can be jointly characterized by a few features including delay spread, channel correlation type, and Doppler spread, among others. Let’s take delay spread, channel correlation type, and Doppler spread these three features as an example. Assuming the WCT considered are AWGN with low correlation (and 0 Hz Doppler Spread), EPA5 with low correlation, EPA5 with high correlation, EVAV700 with low correlation, and EVAV700 with high correlation, then there are three delay spread values, two channel correlation values, and three Doppler spread values. The labels for the three delay spread values are [1 0 0], [0 1 0], and [0 0 1], the labels for the two correlation values are [1 0] and [0 1], and the labels for the three Doppler spread values are [1 0 0], [0 1 0], and [0 0 1]. Finally, the labels for each characteristic are concatenated into an $8 \times 1$ vector to form the overall label for multi-task (three-task in this case) learning.

C. DNN Architectures

A paradigm of the DNN employed in this work consists of five fully-connected layers: one input layer, three hidden layers, and one output layer. The dimension of the input layer is $2N_{\text{des}} \times 1$. The numbers of neurons in the three hidden layers are not definite and are subject to optimization based on a series of other parameters such as the number of input samples which is in turn determined by the amounts of SNRs, slots, WCTs, as well as training and inference data, among
Algorithm 2 Multi-Task Classification

1: Generate training and inference data sets: identical to Steps 1-11 in Algorithm 1
   ▷ Labeling of training and inference data begins
2: Among all the WCTs to be classified, find the numbers of distinct delay spread, channel correlation, and Doppler spread types, denoted as $N_{DS}$, $N_{corr}$, and $N_{Dopp}$, respectively.
3: Create three identity matrices $I_{N_{DS} \times N_{DS}}$, $I_{N_{corr} \times N_{corr}}$, and $I_{N_{Dopp} \times N_{Dopp}}$, then the labels for the $n_{DS}$-th delay spread, $n_{corr}$-th correlation type, and $n_{Dopp}$-th Doppler spread are the one-hot vectors $e_{DS} = [I_{N_{DS} \times N_{DS}}]_{:, : n_{DS}} \in \mathbb{R}^{N_{DS} \times 1}$, $e_{corr} = [I_{N_{corr} \times N_{corr}}]_{:, : n_{corr}} \in \mathbb{R}^{N_{corr} \times 1}$, and $e_{Dopp} = [I_{N_{Dopp} \times N_{Dopp}}]_{:, : n_{Dopp}} \in \mathbb{R}^{N_{Dopp} \times 1}$, respectively.
4: The label for the WCT comprising the $n_{DS}$-th delay spread, $n_{corr}$-th correlation type, and $n_{Dopp}$-th Doppler spread is $e = [e_{DS}, e_{corr}, e_{Dopp}] \in \mathbb{R}^{(N_{DS} + N_{corr} + N_{Dopp}) \times 1}$
   ▷ The dimensions of the labels for training and inference data sets are $(N_{DS} + N_{corr} + N_{Dopp}) \times \alpha N_{WCT} N_{slot} N_{SNR}$ and $(N_{DS} + N_{corr} + N_{Dopp}) \times (1 - \alpha) N_{WCT} N_{slot} N_{SNR}$, respectively.
5: Labeling of training and inference data ends
6: Use the aforementioned training data set and inference data set to train a DNN offline to obtain a trained DNN
7: Among all the WCTs to be classified, find the numbers of unique values for the $f_{DS}$-th delay spread, $f_{corr}$-th correlation type, and $f_{Dopp}$-th Doppler spread
8: The dimensions of the labels for training and inference data sets are $(N_{DS} + N_{corr} + N_{Dopp}) \times \alpha f_{WCT} f_{slot} f_{SNR}$ and $(N_{DS} + N_{corr} + N_{Dopp}) \times (1 - \alpha) f_{WCT} f_{slot} f_{SNR}$, respectively.
9: The dimensions of the labels for training and inference data sets are $(N_{DS} + N_{corr} + N_{Dopp}) \times \alpha f_{WCT} f_{slot} f_{SNR}$ and $(N_{DS} + N_{corr} + N_{Dopp}) \times (1 - \alpha) f_{WCT} f_{slot} f_{SNR}$, respectively.
10: Labeling of training and inference data ends
11: Use the aforementioned training data set and inference data set to train a DNN offline to obtain a trained DNN

To demonstrate the viability and effectiveness of the proposed DNN-based WCT determination algorithms, we have performed simulations using the SRS [1], [3]. The simulation settings are given in Table I. The corresponding simulation results for a single-task DNN and a multi-task DNN are shown in Table II and Table III respectively. It is evident from Table II that the proposed single-task DNN is able to distinguish the given five WCTs with high accuracy (around 90%). Furthermore, Table III demonstrates that the proposed multi-task DNN can successfully categorize the channel fea-

TABLE I: Simulation settings for WCT recognition using DNN.

| Parameter                  | Value                                      |
|----------------------------|--------------------------------------------|
| Number of SRS symbols      | 2                                          |
| Number of RBs              | 16                                         |
| Dimension of each input sample | 768 x 1                                    |
| Number of SNRs             | 31 (0 dB to 30 dB in increments of 1 dB)   |
| Number of slots per SNR    | 500                                        |
| Number of WCTs             | 5                                          |
| WCTs                       | AWGN, EPA5 low correlation, EPA5 high correlation, EVAs low correlation, EVAs high correlation |

TABLE II: Simulation results for single-task DNN corresponding to the simulation settings in Table I.

| Task                              | WCT                                |
|-----------------------------------|------------------------------------|
| Input dimension of training data set | 768 x 69750                      |
| Output dimension of training data set | 5 x 69750                       |
| Input dimension of inference data set | 768 x 7750                      |
| Output dimension of inference data set | 5 x 7750                       |
| Classification Accuracy          | 90.0%                             |

IV. SIMULATION RESULTS

To demonstrate the viability and effectiveness of the proposed DNN-based WCT determination algorithms, we have performed simulations using the SRS [1], [3]. The simulation settings are given in Table I. The corresponding simulation results for a single-task DNN and a multi-task DNN are shown in Table II and Table III respectively. It is evident from Table II that the proposed single-task DNN is able to distinguish the given five WCTs with high accuracy (around 90%). Furthermore, Table III demonstrates that the proposed multi-task DNN can successfully categorize the channel fea-

others. Fig. 1 illustrates an example of the single-task DNN used in our work, in which the dimension of the output layer is $N_{WCT} \times 1$. An example of the multi-task DNN is depicted in Fig. 2 where the output layer contains the labels for multiple tasks and has a dimension of $\sum_{n_{f_{DS}}} K_{n_{f_{DS}}} \times 1$, where $N_{f_{DS}}$ is the total number of wireless channel features considered, and $K_{n_{f_{DS}}}$ indicates the number of unique values for the $n_{f_{DS}}$-th wireless channel feature.
TABLE III: Simulation results for multi-task DNN corresponding to the simulation settings in Table II

| Task                        | Delay spread/Frequency selectivity | Channel correlation | Doppler spread |
|-----------------------------|------------------------------------|---------------------|----------------|
| Input dimension of training data set | 768 × 69750                      |                     |                |
| Output dimension of training data set | 3 × 69750                        | 3 × 69750           | 2 × 69750      |
| Input dimension of inference data set | 768 × 7750                       |                     |                |
| Output dimension of inference data set | 3 × 7750                        | 3 × 7750           | 2 × 7750      |
| Classification Accuracy    | 95.0%                             | 88.6%               | 99.9%          |

tures with high accuracy for all the tasks given. In addition to the performance, it is noteworthy that the training time is relatively short based on our observations. For instance, with five WCTs and the data dimensions listed in Tables II and III, the training time is only 15 to 20 minutes for both single-task and multi-task DNNs to achieve satisfactory classification accuracy as shown in those tables.

V. CONCLUSION

In this work, we have proposed two novel WCT determination algorithms leveraging deep learning techniques, where the original WCT determination problem is formulated as a classification problem with single or multiple tasks. Simulation results show that the proposed algorithms can determine the WCT instantaneously with high accuracy, thus saving a large amount of time and energy spent on trial and error to characterize the WCT in field tests and deployment for next-generation wireless systems.

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