Received 20 October 2023; revised 16 November 2023; accepted 25 November 2023. Date of publication 29 November 2023; date of current version 30 January 2024.

Digital Object Identifier 10.1109/OJAP.2023.3337494

User Effects on Mobile Phone Antennas: Review and Potential Future Solutions

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ABSTRACT This paper explores the significant impact of human proximity on antenna design evolution in mobile communication from GSM to LTE and future 5G technologies. It offers a comprehensive view of the challenges posed by human interactions in current antenna designs, alongside modern solutions to mitigate these issues. Central to our study is the crucial role of extensive data acquisition in enabling AI-driven methodologies. We emphasize the need for diverse and comprehensive datasets to refine AI models. Our research demonstrates notable achievements, with our deep neural network-based models reaching up to 90% accuracy in radiation pattern classification and 87.5% in angular delay profile categorization. These results underscore our proficiency in incorporating AI into antenna engineering. We trace the historical trajectory of user-induced antenna challenges and their current implications, illustrating a coherent progression. This narrative underscores the parallel evolution of antenna designs and user interactions, enhanced by our advanced model classification techniques. Our work presents an efficient method to address user effects using cutting-edge machine learning algorithms.

INDEX TERMS Mobile communication, antenna design, user effects, AI, performance optimization, data acquisition, deep learning, radiation pattern recognition, user proximity, mitigation strategies.

I. INTRODUCTION

ANTENNAS, key components in wireless communication systems, face performance challenges due to user proximity. This issue, rooted in the early days of mobile phones, has grown with technological advancements in mobile communications. Modern mobile terminals integrate multiple antennas on a single platform, all susceptible to user influence [1].

The evolution from GSM to LTE and the increasing reliance on handheld devices like smartphones and tablets have intensified concerns about human body interference with antenna functionality [2], [3], [4], [5]. Research highlights body loss as a crucial factor, particularly in sub-6 GHz frequency bands, where the human body absorbs electromagnetic energy from antennas [6], [7]. This absorption and other effects, such as changes in radiation patterns and efficiency, have been extensively studied [8].

With 5G's emergence, particularly the adoption of millimeter waves (mmWave), user impact on antennas has become a critical research area [9], [10], [11]. Studies suggest that user proximity significantly affects antenna gain, with mmWave beamforming identified as a potential countermeasure [12], [13].

Looking ahead to 6G networks, challenges like user blockage are expected to intensify with the exploration of Terahertz bands above 100 GHz [14]. Potential solutions, including reconfigurable intelligent surfaces (RISs) and innovative beamforming circuits and antennas, are being investigated to address these obstacles [15].

Artificial Intelligence (AI) integration in mobile systems emerges as a promising approach to address user shadowing and other antenna-related challenges. Machine learning, deep learning, and thermal imaging techniques are being leveraged to predict and mitigate user effects on antenna performance. Convolutional neural networks (CNNs) and explainable artificial intelligence (XAI) are particularly notable for training models that can identify shadowing or blockage in antenna radiation patterns [14], [16], [17].

This study rigorously examines the impact of human interaction on the evolution of antenna performance, highlighting the evolution from historical developments to current challenges and advancements. We particularly focus on user blockage in future mobile communication systems and explore solutions integrating AI with antenna design. The paper is organized as follows: Section II discusses User Effects in Mobile Communication from the GSM era to LTE. Section III addresses User Effects on Mobile Terminal Antennas in 5G mmWave deployments. Section IV explores User Blockage Challenges for frequencies beyond 5G and into 6G. Section V delves into machine learning algorithms applied to User Effects. Section VI presents a deep neural framework for handset antenna position classification, utilizing radiation pattern datasets. Section VII discusses antenna position classification using wideband radio channel propagation datasets. Finally, Section VIII concludes with a synthesis of our findings. This structure provides a comprehensive and forward-looking overview of the field, merging historical insights with contemporary technological advancements.

II. USER EFFECTS ON MOBILE COMMUNICATION BEFORE 5G

In the past, mobile communication technology at the sub-6 GHz bands has been advancing rapidly, leading to an increase in the number of hand-held devices such as smartphones, laptops, and tablets. However, the use of these devices raises concerns about the effect of the human body on the performance of the antenna. One of the most significant effects of the human body on mobile terminal antennas is body loss. Body loss occurs when the human body absorbs a portion of the electromagnetic energy transmitted by the antenna. In the early history of the handheld mobile devices, Toftgard et al. [3] investigated the effects of the presence of a person on portable antennas. A simple, very basic head and hand phantom was introduced in Fig. 1(a) and it has been found that the impedance and radiation pattern of antenna were affected by the presence of a person as shown in Fig. 1(b) and Fig. 1(c). Noticeably, the difference between simulated and measured results are significant as the simulation tools were quite primitive at the time.

A few years later, Pedersen et al. [18] conducted studies measuring the mobile phone antennas with the human in different positions on the floor of the building while measuring the average received power as shown in Fig. 2(a). Large variations of the average received power between the positions were observed at every floor of the building and worst for the third floor as shown in Fig. 2(b).

Then in Nielsen et al. [8], the statistics of body loss for mobile phones operating in the UHF frequency range were modeled by a Gaussian distribution. Boyle [19] investigated the performance of GSM 900 antennas in the presence of people and phantoms. The example of the measurement with a person is shown in Fig. 2(c). The author found that the presence of people and phantoms caused a significant reduction in the antenna efficiency, particularly when the antenna was placed near the head in Fig. 2(d).

In next study by Krogerus et al. [20], the authors analyzed the effect of the human body on the total radiated power and

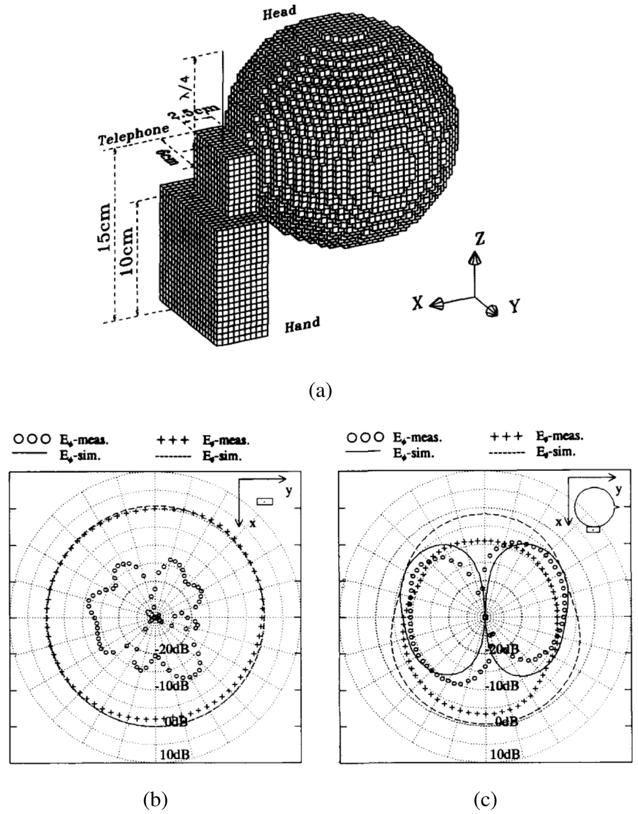


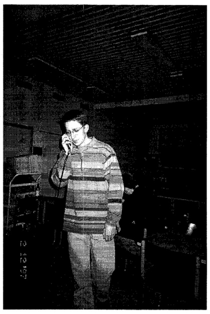
FIGURE 1. Proposed head and hand phantom in (a), radiation pattern of the phone in free space in (b) and with a phantom/human in (c) [3].

the 3-D radiation pattern of mobile handsets for multiple users for the first time Fig. 3(a) and different phone grips were considered. They found that the presence of the human body caused a reduction in the total radiated power and the radiation patterns appeared differently for each user as shown in Fig. 3(b) from the omnidirectional in free space to highly directional with the human.

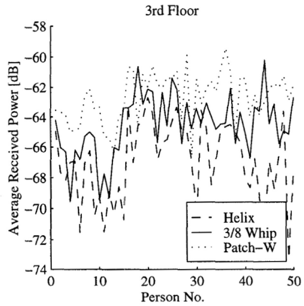
Krogerus et al. in [21] continued experiments using a 3D far-field pattern measurement system and imaging phantoms to further investigate the effect of the human body on the radiation patterns of GSM mobile handsets and found that body loss (BL) caused by the human body can lead to changes in the antenna radiation patterns and total radiated power (TRP) of mobile handsets.

In addition, Pelosi et al. examined the antenna proximity effects for talk and data modes in mobile phones [22]. They used computer-aided design (CAD) simulation and measured the total radiated power and radiation patterns of the antennas for different phantoms. At that time, more complex models for human hand Fig. 4(a) and head Fig. 4(b) had been proposed, and now looked more anatomically correct, but still quite rough. The study found that the user's grip caused significant variations in the antenna's performance and caused variations in absorption loss on different parts of antenna in Fig. 4(c).

In Ilvonen et al. [23], the effect of antenna dimensions and locations on mobile terminal antenna performance were



(a)



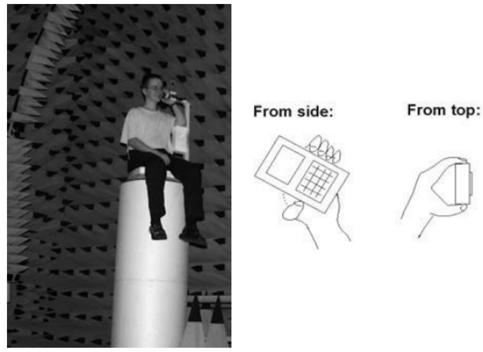
(b)

(c)

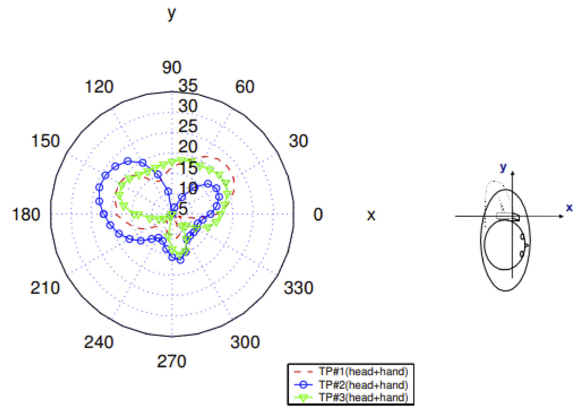
	PIFA-1	PIFA-2	PIFA-3	Helix	Flip
People	-11.3	-14.7	-15.3	-12.8	-12.4
Phantoms	-11.8	-10.6	-14.9	-11.2	-11.5
Difference	-0.5	4.1	0.4	1.6	0.9

(d)

FIGURE 2. **User under measurement while holding the phone naturally in (a), and average received power measured for the 3rd floor in (b) [18], (c) User under measurement in the anechoic chamber and (d) the results of the measured loss [8].**



(a)



(b)

FIGURE 3. **User under the measurement and phone grips (a), radiation pattern of antenna measured with the user. Notice here the antenna radiation pattern is plotted in terms received power [20].**

measured. They found that the Q-factor and the efficiency of the antenna were significantly affected by the user's hand. Hereafter, Nielsen et al. [24] investigated the effect of the human body on the total radiated power and the 3-D radiation pattern in the typical environment Fig. 5(b) with multiple different headset types. Now with the emergence of the faster communications speeds, the users begin to use their phones for many other things than talking, thus data mode grip types were investigated as well Fig. 5(b).

One of the first measurements campaigns investigating the body loss for popular thin smartphones was done by Tatomirescu and Pedersen [25], which confirmed again that a hand had a significant effect on the antenna performance, causing a reduction in the antenna efficiency for all popular smartphones. Then in Andersen et al. [26], a similar study concluded that the body loss was higher than expected for devices such as laptops, tablets, and smartphones, when operating at 900 MHz band in contrast to the 1900 MHz band. Finally, in the recent years, the standard measurement setups were defined by the 3GPP community, which were used to measure the popular smartphones in Zhekov and Pedersen [27]. In Fig. 6, the four defined measurement setups are shown. Furthermore, the performance of the popular smartphones did not improve from six years earlier [25].

Over the years, both measurements and simulations have been used to study the effects of users on mobile phone antennas. Observably, holding the phone close to the head can cause significant changes in the radiation pattern of the antenna. Additionally, absorption loss varies depending on factors such as the user's grip, distance from the head, and antenna type and position of the phone. The presence of the user can also result in antenna detuning, adding mismatch loss to total antenna losses. To facilitate more efficient simulation and measurement studies of user effects on mobile phones, accurate phantoms and simulation models have been developed.

III. USER EFFECTS ON MOBILE TERMINAL ANTENNAS FOR 5G mmWAVE APPLICATIONS

Frequencies in the range from 23.5 to 47 GHz, have become increasingly important for mobile communication systems, especially for 5G networks in recent years. However, these frequencies present several challenges that need to be overcome in order to provide reliable and efficient communication. First, the blockage from objects becomes more severe at higher frequencies, which can lead to significant signal attenuation and outage in the communication link. Another challenge is related to the radiation pattern of the mobile

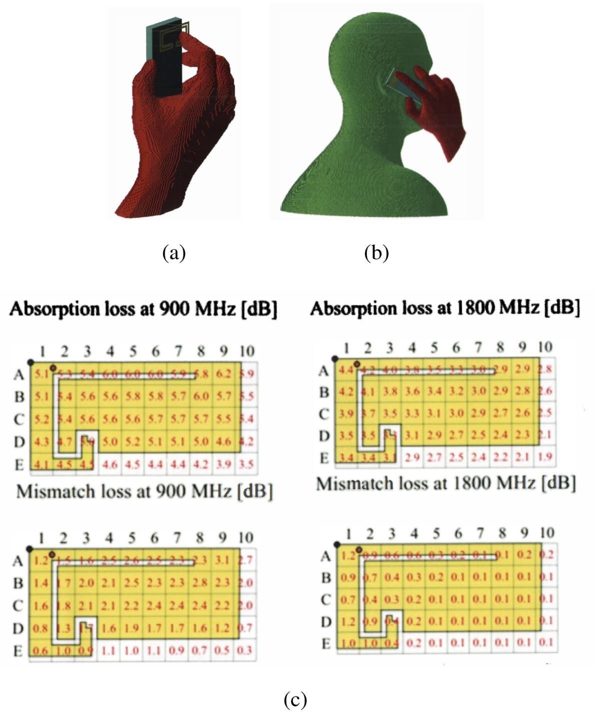


FIGURE 4. **Anatomically correct models for human hand (a) and for human head with a hand in (b), and absorption loss displayed on the PIFA mobile antenna structure in (c) [22].**

FIGURE 5. **The measurement environment with the base station and mobile station locations in (a) and typical used grips in (b) [24].**

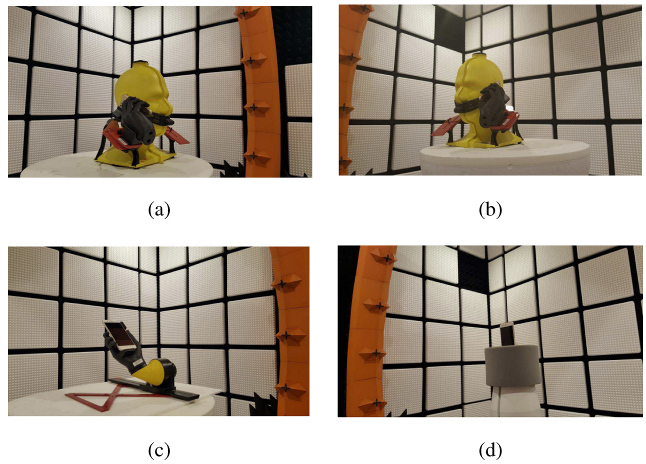


FIGURE 6. **The defined measurement setups: head and hand - right side in (a), head and hand - left side in (b), hand and phone in (c), and free space in (d) [27].**

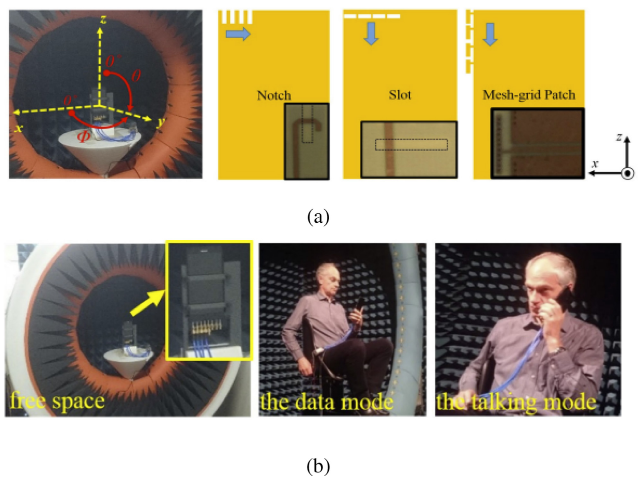


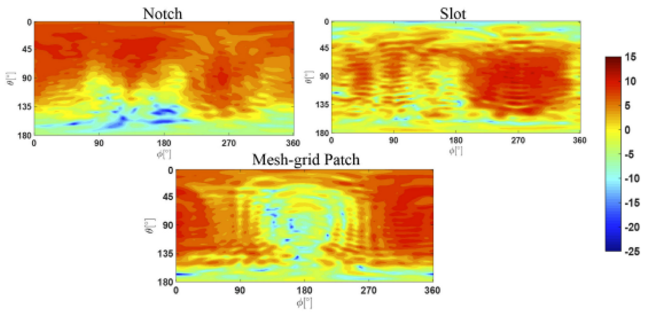
FIGURE 7. **Measurement setup in free space in (a) and with the user in (b) [30].**

antennas. At mmWave frequencies, the required radiation pattern becomes highly directional in order to counteract for the high path loss, thus the antenna needs to be accurately pointed towards the receiver for efficient communication. To overcome these challenges, mmWave beamforming has been proposed as an enabling technology for 5G cellular communications by Roh et al. [28].

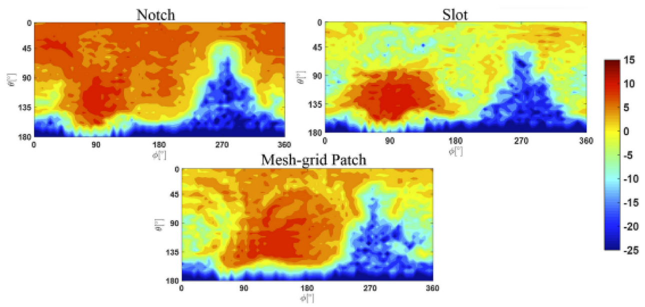
Even back in 1986 the absorption of mmWave by human beings and its biological implications were investigated by Gandhi and Riazi [29]. The study showed that the absorption of mmWave by human beings is frequency-dependent and varies with the body's size, shape, and composition. The advent of 5G communication systems has led to a significant increase in research on the effects of users on mobile terminal antennas. Zhao et al. [30] investigated the effect of the user's body on phased arrays in the user equipment for 5G mmWave communication systems. However in this study only a single antenna element was studied at 28 GHz. The three different antennas are shown in Fig. 7(a) and the measurement system with the user in Fig. 7(b). The measured radiation patterns are clearly showing the user blockage in Fig. 8(a) and Fig. 8(b). The study showed that the user's body can affect the performance of the mmWave mobile antenna, resulting in a severe user shadowing, but the measured body loss is extremely low Fig. 8(c) in comparison to the pre-5G studies.

Next, Syrytsin et al. [13] conducted a statistical investigation of the user effects on mobile terminal antennas for 5G applications for 12 users. The measurement setup for one of four studied grips is shown in Fig. 9(a). The study showed that the user's effect on the antenna can be modeled by a log-normal distribution, and the standard deviation of the distribution varies with the frequency and polarization of the antenna. Furthermore, the variance in body loss between the users is shown to be low in comparison to the sub-6G frequencies Fig. 9(b).

Zhang et al. [31] proposed a planar switchable 3D-coverage phased array antenna for 28 GHz mobile terminal applications. The antenna provides a flexible coverage area



(a)

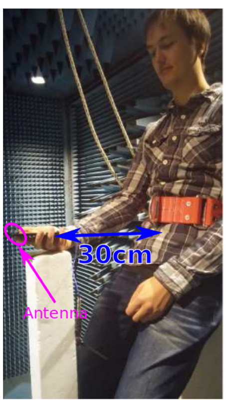


(b)

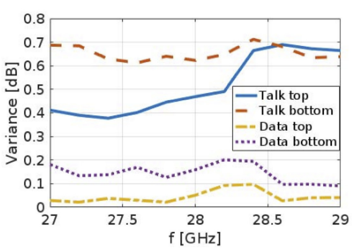
	Notch	Slot	Mesh-grid patch
FS	–0.2 dB	–1 dB	–0.5 dB
Data	–0.5 dB	–2.5 dB	–2 dB
Talking	–2 dB	–3.5 dB	–2.2 dB

(c)

FIGURE 8. Radiation pattern of antennas in free space in (a), with the user in (b), and the measured body loss of different antennas in (c) [30].



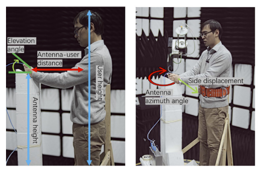
(a)



(b)

FIGURE 9. Measured users in (a) and measured variance in the body loss between the users [13].

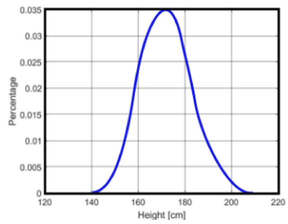
and can switch between a directional and an omnidirectional pattern. The study found that the user's position and orientation can significantly affect the antenna's radiation pattern and the received power. Liu et al. [32] found that the most critical user gestures are few and could be measured and modelled as Fig. 10(a). The measurement campaign



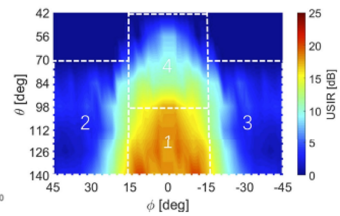
(a)

(b)

FIGURE 10. Most crucial gestures which affect the user blockage in (a) and user orientations used for measurement campaign in (b) [32].



(a)



(b)

FIGURE 11. Height distribution between the users in (a) and modelled user shadowing pattern in (b) [32].

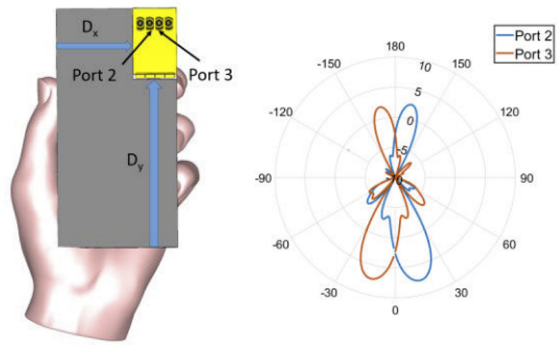


FIGURE 12. The proposed phased antenna array location in and radiation patterns for two ports on the antenna [12].

was conducted with 18 subjects with a Gaussian height distribution Fig. 11(a) and the gestures used for the measurement shown in Fig. 10(b). A stochastic user shadowing model using measurements with multiple users and different gestures, valid for frequencies from 28 to 34 GHz shown in Fig. 11(b). The model is based on a random Gaussian process and based on the measured results, with a more realistic shape and distribution in the shadowing region than the 3GPP self-blocking model, and has an accuracy of 2 dB independent of antenna type and polarization.

Finally, Liu et al. [12] investigated user shadow intensity suppression of the handset antenna shown in Fig. 12 at 28GHz in data mode. The top corner close to the hand is found to be more beneficial in increasing power intensity in the body shadow region. Both top corners are suggested as antenna placement to effectively reduce the deterioration caused by human blockage.

The inclusion of antennas in handsets operating at 5G frequencies results in severe user blockage. In addition, body blockage is a more significant issue than body loss. However, the placement of mobile phased arrays on mobile phones can partially address body blockage. For this purpose, it is essential that the antenna is directed towards the user to induce surface waves [12], which can potentially enhance the power in the shadowing region located behind the user. We can clearly see the need for the accurate dynamic full-body human phantoms for the measurement applications at 5G frequencies.

IV. CHALLENGES OF USER BLOCKAGE AT FREQUENCIES HIGHER THAN 5G FREQUENCIES IN 6G COMMUNICATIONS AND BEYOND

As mobile communication technology continues to evolve, in all likelihood the user effects will still pose challenges for antenna designers. The sixth-generation (6G) mobile communication system is being actively pursued worldwide to satisfy extreme-high-speed communication. The first-generation of mobile telecommunications was deployed over four decades ago. Since then, wireless communication technology has evolved at a dramatically fast pace. The current fifth-generation (5G) holds great promise in providing an ultra-fast data rate, a very low latency, and a significantly improved spectral efficiency [33]. However, in the years beyond 2030, newly emerging data-hungry applications and the greatly expanded wireless network will call for the sixth-generation (6G) communication that represents a significant upgrade from the 5G network, covering almost the entire surface of the earth and the near outer space [33]. In both the 5G and future 6G networks, mmWave technologies will play an important role in accomplishing the envisioned network performance and communication tasks [33]. To achieve the extreme-high-speed communication envisioned for 6G, terahertz bands above 100 GHz are being considered, as a wider frequency bandwidth can be utilized than in 5G [34]. However, at these high frequencies, the problem of user blockage becomes a major challenge for 6G communications Fig. 13. However, we know that when the antenna is held by the user then the blockage becomes even worse as shown repeatedly in 5G studies. The propagation characteristics of terahertz waves are affected by human blockage, building shadowing, and scattering effects from rough building surfaces [34]. In 6G networks, the use of higher frequencies requires a denser deployment of base stations to maintain connectivity [35]. However, this denser deployment can lead to increased user blockage, resulting in a decrease in network performance and reliability [35]. Therefore, mitigating the effects of user blockage is critical for the success of 6G communications. The challenges of user blockage in 6G communication systems are expected to operate at higher frequencies than their predecessors, with the possibility of utilizing terahertz (THz) bands above 100 GHz, due to the wider frequency bandwidth available in these regions. However, one of the major challenges associated with operating at such high frequencies is the increased likelihood of user blockage. Human blockage,

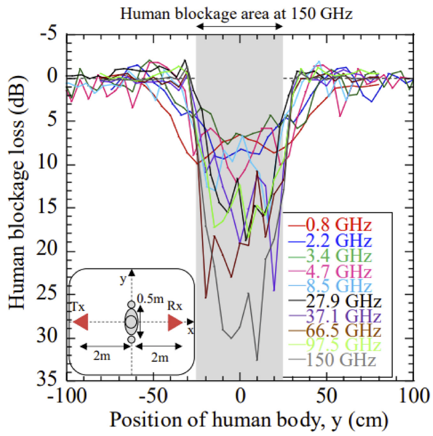


FIGURE 13. The user blockage measured in the anechoic chamber [35].

building shadowing, and scattering effects can all contribute to significant losses in signal strength at frequencies above 100 GHz. One potential solution to mitigate user blockage in 6G systems is the use of reconfigurable intelligent surfaces (RISs). RISs are essentially flat surfaces made up of many small elements that can be controlled to reflect incident electromagnetic waves in specific directions. By strategically placing RISs in 6G networks, it may be possible to redirect signals around obstacles and reduce the impact of user blockage. Additionally, beamforming integrated circuits and antennas can be designed to expand the beamforming area, which can also help to mitigate the effects of user blockage.

V. MACHINE LEARNING METHODS AND USER EFFECTS

With the better integration of AI within the fields of electromagnetism, antennas and mobile communications, AI could be used to classify, identify and overcome the user shadowing by creating the intelligent smart phone antenna designs. One of the promising approaches to mitigating user effects on antennas is the use of machine learning and deep learning. Let us review the state-of-the-art techniques that have been developed to leverage AI in antenna design and optimization. In order to develop effective AI models for antenna design, large amounts of high-quality data is required. Antenna design has become increasingly complex due to the ever-increasing demands of modern wireless communication systems. Traditional methods of accounting for user effects have been limited in their accuracy due to the complexity of the interaction between the user and the antenna. However, recent advances in machine learning techniques have shown great promise in accurately modeling user effects on antenna performance. Li et al. [36] provide a comprehensive review of the use of machine learning in electromagnetics, including its applications to biomedical imaging. In the context of antenna design, machine learning techniques could be used to predict the effect of users on the antenna radiation pattern, as demonstrated by Kim and Choi [37] who proposed a deep learning-based approach for radiation pattern synthesis of an array antenna. Deep learning techniques have also been used to design and optimize antennas for mmWave applications. Montaser and Mahmoud [38] propose a deep learning-based antenna design and beam-steering technique that considers the effect of circular polarization on mmWave antennas. The optimization algorithm used in this work is based on the Adam algorithm [39], which is a popular optimization technique in deep learning. Tong [40] proposed a machine learning-based theoretical optimization method for antenna design. This method uses neural networks to predict the electromagnetic properties of antennas, which could theoretically be used to optimize antenna design to account for user effects. Zhou et al. [41] used transfer learning to calibrate multi-element phased antenna arrays, which could be one of the crucial components in achieving accurate beamforming performance. Efficient direction of arrival (DOA) estimation is critical for many wireless communication applications. Chen et al. [16] proposed a new approach based on deep neural networks (DNNs) that achieves high DOA estimation accuracy and reduces the computational complexity required by traditional superresolution DOA estimation methods such as multiple signal classification (MUSIC) and estimation of signal parameters via rotation invariance (ESPRIT). Real-time object detection is an essential component of many wireless communication systems. Wang et al. [42] introduced YOLOv7, a trainable bag-of-freebies that sets a new state-of-the-art for real-time object detectors. YOLOv7 is a variant of You Only Look Once (YOLO), which is a real-time object detection system that uses a single neural network to predict bounding boxes and class probabilities directly from full images in real-time.

Recently, thermal imaging has become a popular tool for recognizing and detecting anomalies in various fields, including medical imaging and remote sensing. With the help of machine learning algorithms, thermal imaging can be used to detect and classify different types of objects and patterns. One possible application of thermal imaging and machine learning is in recognizing shadowing or user blockage in the radiation patterns of antennas. By analyzing the thermal images, we can create a heatmap that represents the distribution of heat in the area of interest, and when applied to the radiation pattern of the antenna with the user would be able to detect/classify high power red regions and low power blue regions (shadow form the user). To recognize shadowing or user blockage in the radiation patterns of antennas, we can use machine learning algorithms to analyze it as a heatmap. For example, we can use convolutional neural networks (CNNs) to classify different types of patterns in the heatmap. In a study by Samek et al. [43], the authors used CNNs to evaluate the visualization of what a deep neural network has learned. Another approach is to use explainable artificial intelligence (XAI) techniques to identify the features that are important for the classification. For example, Meng et al. [44] used complementary heatmap and attention-explore loss to detect retinal diseases. The authors used Grad-CAM to generate complementary heatmaps that highlight the regions that are important for the classification. In a study by Wu et al. [45], the authors proposed a unified framework for automatic detection of wound infection with artificial intelligence. The framework includes a deep learning algorithm that uses thermal images to detect wound infections. These approach could be potentially adapted to classify the user shadowing.

Heat maps are an integral visualization tool in antenna and propagation studies, adept at portraying complex data in an easily interpretable form. In antenna domains, they are instrumental for presenting 3D radiation patterns, converting intricate radiation characteristics into visually intuitive representations. This allows for a rapid assessment of an antenna's performance across various spatial orientations, highlighting key aspects such as distributions of E and H fields on the antenna surface and identifying potential hotspots or inefficiencies. The upcoming Section VI delves into the application of neural networks for classifying these radiation patterns, including user effects.

Similarly, in propagation studies, heat maps are invaluable for depicting angular delay profiles of specific propagation channels. They provide a clear visualization of the multi-path phenomenon, representing the density and directionality of incoming rays. This elucidates signal travel, reflection, and refraction within various environments, a topic that is explored in greater depth in Section VII with respect to the classification of power delay profiles using deep neural networks. In exploring the efficacy of heatmaps for neural network inputs, Gupta et al.'s study [46] on mmWave FMCW radar data classification using machine learning on range-angle images provides a compelling precedent, demonstrating how heatmap visualizations can significantly enhance the classification accuracy of complex environmental data.

Incorporating these heat map images directly into neural network models, particularly in AI-driven classifications, harnesses their rich, multidimensional data in a format that is both recognizable and interpretable by the network. Neural networks, especially convolutional layers, are proficient at extracting features from image-based data. This approach aligns closely with traditional methods of analyzing antenna and propagation data and can enhance the training process's intuitiveness and accuracy. By leveraging heat maps, as demonstrated in the works of Bruno and Calimeri [47], Samek et al. [43], and Shang et al. in [48], we can significantly improve the network's ability to simulate expert-like decision-making in antenna and propagation scenarios. These studies collectively support the notion that heat maps serve as an effective alternative to raw data in AI classifications, offering a more efficient and interpretable approach, particularly in complex decision-making tasks.

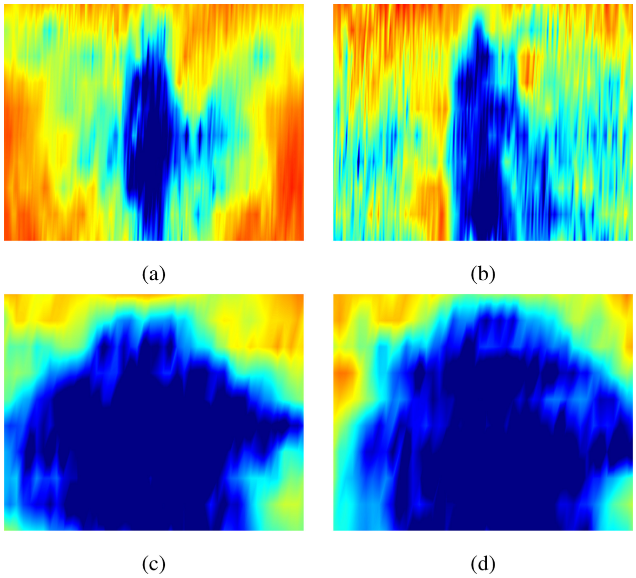


FIGURE 14. Image of the radiation pattern of the user with full antenna radiation pattern (a) top antenna and (b) bottom antenna, and the radiation pattern of the shadow region (middle ±45 degree) for (c) top antenna and (d) bottom antenna.

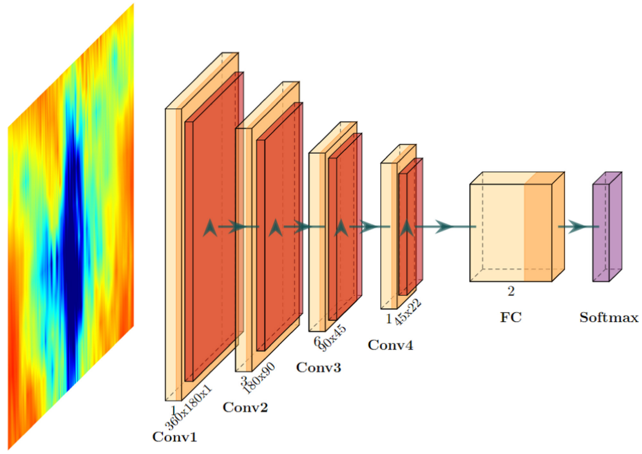


FIGURE 15. A simple deep learning network architecture.

VI. HANDSET ANTENNA POSITION CLASSIFICATION FROM RADIATION PATTERN DATA

We propose a simple neural network to classify antennas based on their radiation patterns, taking into account user effects as one of the examples of how machine learning can aid the user effect studies in the future. The data set used in the study is based on measurements from Syrytsin et al. [13], consisting of only 12 subjects but with 11 frequency points for each measurement. The network is trained on a set of training data (11 users and 6 frequencies), validated on a separate set of validation data (11 users and 5 frequencies), and tested on a separate set of test data (the 12th user and all 11 frequency points). The objective of the study is to identify the top or bottom antenna from the radiation pattern data, cutting out the shadowing from the full antenna pattern and using it for classification as well. In Fig. 14(a) we can see the radiation pattern image for the top antenna and in Fig. 14(b) for the bottom antenna. visually the two can be distinguished, however the more we reduce our observation angle, the more similar the two patterns look. If the observation angle is reduced to the 90 degrees as in the model from Liu et al. [32], then we can see an example of the radiation patterns for the top and bottom antenna which look extremely similar to each other as shown in Fig. 14(c) and Fig. 14(d) respectively.

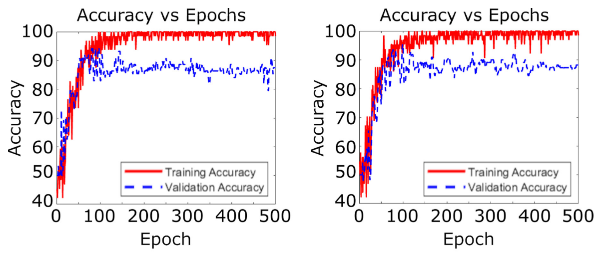
In our proposed neural network design, as illustrated in Fig. 15, the starting point is the image input layer, which is specifically designed to accept image data. Following this are four convolutional layers (Conv1 - Conv 4) which work to extract specific features or patterns from the image. These convolutional layers are immediately followed by ReLU (Rectified Linear Unit) activation layers, introducing non-linearity, helping the network to learn complex patterns. The ReLU activation function is a type of activation function commonly used in neural networks. It outputs the input directly if it is positive; otherwise, it outputs zero. Max pooling layers are also part of this architecture, and their main role is to reduce the dimensionality of the data, ensuring that the most significant and representative features are retained while discarding the redundant ones.

Towards the end of the network, we have a fully connected layer (FC), which effectively brings together and integrates the previously extracted features. The softmax layer subsequently computes the probabilities associated with each possible output category. Based on these probabilities, the classification layer then makes a final determination on the category or class of the input image.

For the training process, several settings and techniques are employed. The Adam optimizer is a method chosen to adjust the internal parameters of the network to ensure accurate performance. We use an initial learning rate of 0.001 to set the starting pace for these adjustments. The entire dataset will be processed up to 250 epochs, and in each iteration, groups of 64 images, termed as mini-batches, are processed collectively.

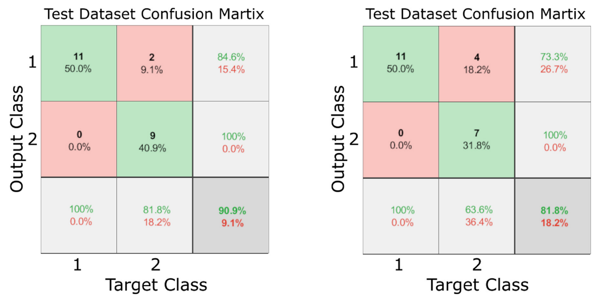
Lastly, to enhance the robustness of the network and prevent a phenomenon called overfitting, where the network becomes too tailored to the training data and performs poorly on new data, we've incorporated a method known as dropout. This involves periodically and randomly deactivating certain neurons during the training process.

The training and validation data are loaded from external data files. The test data is defined using two sets of antenna images for the top and bottom positions of the phone pointing away and towards the user, respectively. These images are resized to a spatial resolution of 360x180 pixels for the full antenna radiation pattern data-set and to the 90x180 pixels for the shadow region data-set, representing a resolution of 1 degree in phi and theta. The trained network is then used to classify the test data, and the accuracy of the predictions is calculated by comparing the predicted labels with the actual labels. The accuracy and loss over epochs are plotted



(a) (b)

FIGURE 16. The accuracy and loss over epochs for (a) 360x180 pixels for the full antenna radiation pattern data-set and (b) the 90x180 pixels for the shadow region data-set.



(a) (b)

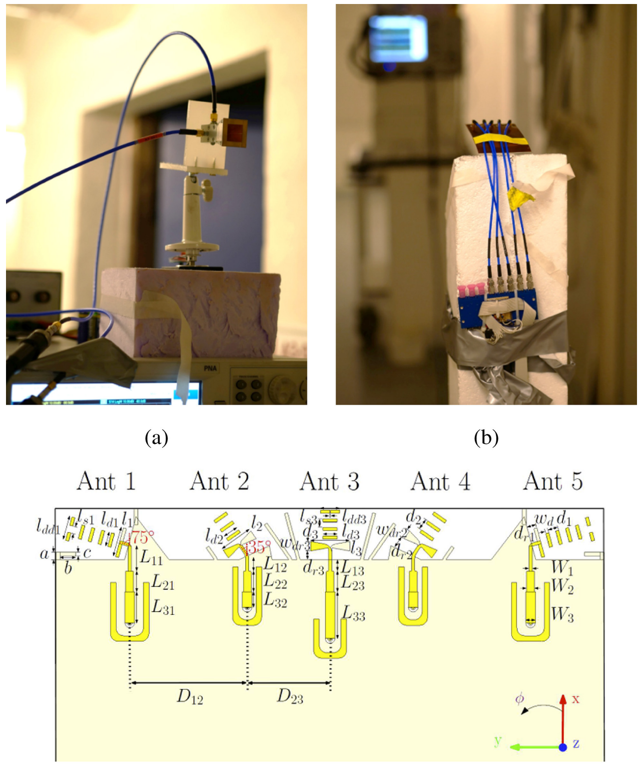
FIGURE 17. The confusion matrix for (a) 360x180 pixels for the full antenna radiation pattern data-set and (b) the 90x180 pixels for the shadow region data-set.

in Fig. 16(a) for the full radiation pattern of antenna and in Fig. 16(b) for the data-set for the shadow region. The confusion matrix is shown in Fig. 16(a) showing achieved 90.9% accuracy for the full antenna pattern and 81.8% for the shadow region. This result show that even with a limited data-set the antennas can be classified with the presence of the user. So with a larger data-set, the accuracy of the classification can be increased.

VII. HANDSET ANTENNA POSITION CLASSIFICATION FROM PROPAGATION DATA

A. MEASUREMENT CAMPAIGN

Our measurement campaign was planned to garner a dataset that captures the complexities of 5G signal behavior. Using a base station's (BS) dual-polarized horn antenna at the height of 1.5 m, capable of rotation in the azimuth plane, we implemented a sweeping mechanism across a predetermined angular range as shown in Fig. 18(a). This scanning was conducted in 20° steps, resulting in 10 distinct angular points. In essence, the generated angular delay profile represents the power of a received signal as it varies with both time delay and angular orientation, thus offering a multi-dimensional insight into channel characteristics. For the mobile station we have employed the yagi-uda 5G mmWave mobile array with a wide bandwidth, which have been designed in Di Paola et al. [49] and shown in Fig. 18(c). The mobile station is used to receive the wide band signal from a Vector Network Generator with a frequency range from 24.25 to 27.5 GHz. Smartphone mock-up is mounted



(a) (b)

(c)

FIGURE 18. Horn antenna base station setup in (a), mobile station setup with an RF switch in free space in (b) and the 5G yagi-uda antenna used in the measurement campaign as a smartphone mobile station mock-up in (c) [49].

on the Styrofoam stand as shown in Fig. 18(b) as the height of 1 meter and idea is that the user is resting his hand on the stand in order to eliminate small involuntary movements from the user.

Spatial resolution in communication systems signifies the capability to discern two closely spaced events. This is paramount as it provides an understanding of the medium's granularity and fidelity. For our measurements, the resolution depends largely on the bandwidth and the number of sampled points. In our case, with a bandwidth of 3.25 GHz and 500 points, the resolution plays a pivotal role in how we interpret and utilize the resulting data.

The basic spatial resolution, derived from the bandwidth, is approximately 4.615 cm. However, the high number of sampling points—500 in our setup—enhances this resolution. With an enhancement factor derived from the square root of the number of points, our effective resolution sharpens to roughly 2.06 mm. This granularity ensures that we can discern minute differences and changes in the measured data, providing a richer and more detailed dataset.

In the rapidly evolving landscape of 5G communications, understanding user-induced effects on antenna performance is paramount for optimized system design and deployment. The collected measurement data, with its high spatial resolution and multi-dimensional angular delay profile, provides

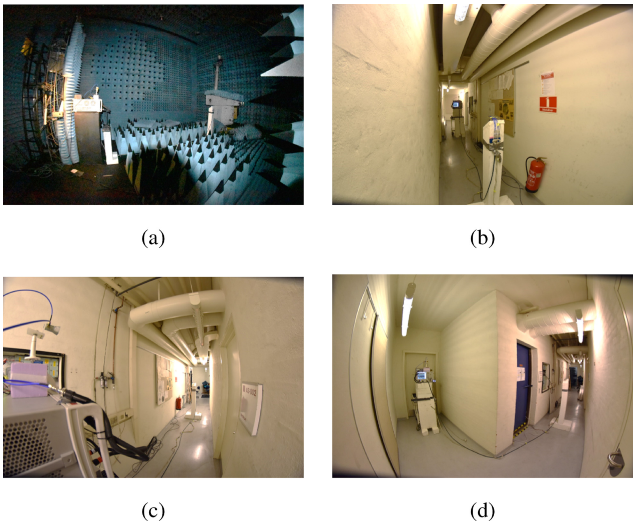


FIGURE 19. Measurement setups in the anechoic chamber in (a), in the corridor seen from the mobile station in (b), in the corridor seen from the base station in (c) and in the corner in (d).

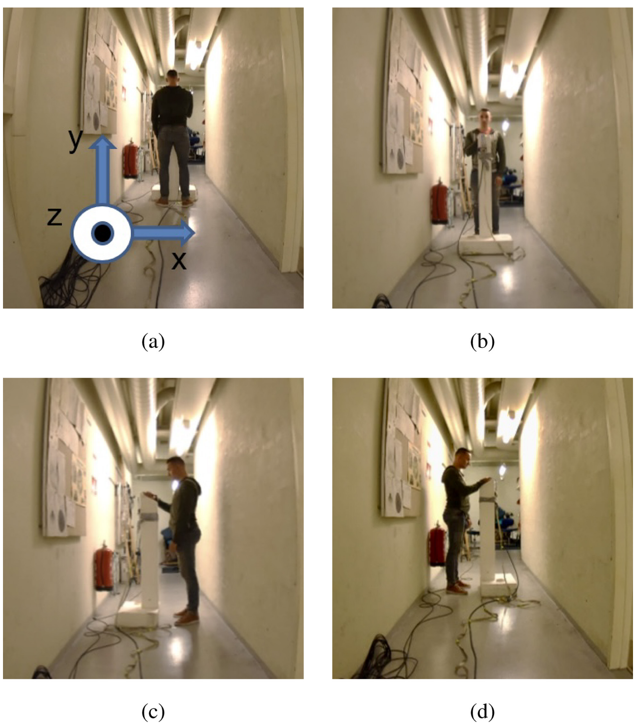


FIGURE 20. User orientation in the measurement campaign back to BS in (a), front in (b), side 1 - left in (c), and side 2 - right in (d).

insights into the complexities of real-world signal propagation impacted by the user's presence and orientation. By analyzing how different user orientations in Fig. 20 —front, back, and both sides—affect the signal's strength and quality, researchers and engineers can tailor 5G antenna designs and communication algorithms to mitigate user-induced signal blockages or reflections. This not only leads to more robust communication links but also enhances user experience by ensuring consistent and high-quality connectivity, even in the most challenging user scenarios.

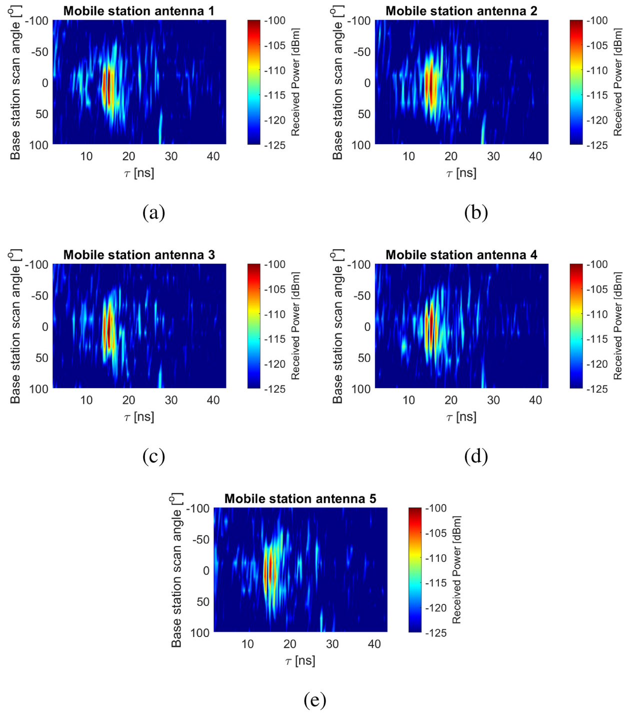


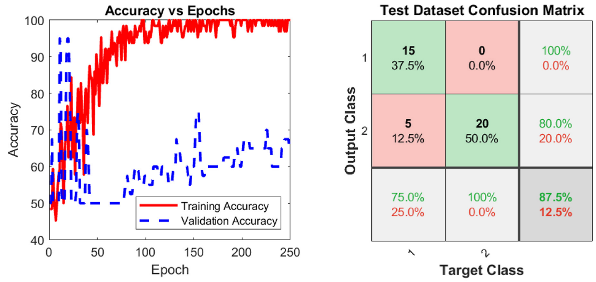
FIGURE 21. An example of angular delay profiles of the corridor propagation channel with the user in front position and the mobile station array located on top measured with (a) antenna 1, (b) antenna 2, (c) antenna 3, (d) antenna 4, and (e) antenna 5.

B. DATA COLLECTION AND NEURAL NETWORK INSIGHTS

We adopted a dual-environment approach for training data collection. The anechoic chamber (Fig. 19(a)) ensured a pristine, controlled environment, while the corridor (Fig. 19(b) and Fig. 19(c)) mimicked realistic propagation scenarios, accounting for multi-path effects, reflections, and user-induced signal changes. Crucially, during the validation phase, we utilized data from NLOS regions in the corner at the end of the corridor (Fig. 19(d)), attempting to replicate the intricate challenges typical of urban environments.

Fig. 21 illustrates the angular delay profiles for five distinct mobile station antennas. These profiles delineate the corridor propagation channel dynamics when the user is positioned in the front orientation as in Fig. 20(b). Each heatmap encapsulates the received signal's strength across varying angular and delay dimensions for the designated antenna.

Incorporating these heatmaps, or the underlying raw data they represent, into a convolutional neural network (CNN) facilitates the classification of antennas based on their unique angular delay profiles. The neural network as delineated in our methodology, as shown in Fig. 15, comprises a sequence of convolutional and max-pooling layers introduced for optimal regularization. Post feature extraction, a densely connected layer outputs the classification predictions. Notably, the dataset embodies 10 distinct Base Station (BS) scan angles, signifying the varying angles at which the BS



(a) (b)

FIGURE 22. Results from the proposed deep neural network on the propagation data-set as Accuracy vs Epochs in (a) and the confusion matrix in (b).

communicates with the mobile terminals. Furthermore, with five heatmaps representing five mobile terminal antennas and two BS antenna polarizations for each configuration, the data dimensionality effectively becomes multifaceted, enriching the training set and amplifying the classification's robustness.

In Fig. 22, the performance of the proposed deep neural network on the propagation dataset is shown. Fig. 22(a) displays a comparison of training and validation accuracy across 250 epochs, with the former approaching near perfection and the latter stabilizing after preliminary fluctuations, hinting at potential overfitting. Fig. 22(b) reveals an 87.5% accuracy in discerning smartphone antenna array positions in a Non-Line-of-Sight (NLOS) setting, despite this dataset being external to the primary training scope. However, the limited dataset size mandates caution. Enhancing the dataset's breadth through additional measurements and varied propagation conditions could increase the model's robustness, preventing overfitting and ensuring heightened predictive fidelity in subsequent applications.

Combining measurement methodologies with a tailor-made neural network design, our system offers invaluable insights to antenna and propagation professionals. Through effectively deciphering angular delay profiles inherent in communication channels, the system adeptly suggests optimal antenna array orientations. This takes into account diverse user orientations and multifaceted environments. Our holistic approach, bridging deep learning with propagation and antenna engineering, paves the way for smarter and more efficient 5G antenna deployment strategies.

VIII. DISCUSSION

In Table 1, we compare the AI methods used in Sections VI and VII for classifying antenna designs. Section VI uses a neural network on radiation pattern data and gets good results (90.9% accuracy for full patterns and 81.8% for shadow regions) even with limited data. This shows that AI is effective for identifying patterns in antenna designs.

Section VII looks at antenna positions using different data from a user-involved study and gets 87.5% accuracy in challenging settings. This highlights how the model can handle real-world situations, which is important for the development of future 5G and 6G networks.

TABLE 1. Comparison of classification methods in Sections VI and VII.

Criteria	Handset Antenna Position Classification from Radiation Pattern Data	Handset Antenna Position Classification from Propagation Data
Data Source	Antenna measurements from 12 subjects with 11 frequency points each	Wideband radio channel propagation datasets from a tri-environmental user-involved measurement campaign
Methodology	classifying top or bottom antenna from radiation pattern data	classifying antenna positions using angular delay profiles
Dataset Characteristics	Limited dataset (11 users, 6 frequencies for training)	Rich dataset from diverse environments including NLOS regions
Results	90.9% accuracy for full antenna pattern, 81.8% for shadow region	87.5% accuracy in discerning smartphone antenna array positions in NLOS setting
Advantages	Effective even with limited data	Effective in diverse complex environments
Limitations	Potential overfitting due to dataset size	Larger dataset required for broader applicability
Applications	Identifying antenna position in presence of user	Suggesting optimal antenna array orientations considering various user orientations

When we look at both methods together, it's clear that AI can be really useful for designing antennas. Each method gives us different insights and could be combined for better antenna designs in the future.

However, there are some challenges. For example, in Section VI, the small amount of data might lead to overfitting, where the model is too tailored to the specific data it was trained on. To make the models more accurate and useful for different situations, we need more and varied data. We could also improve the models by adding more detailed information, like specific parts of 5G mobile antenna systems, into the AI analysis.

IX. CONCLUSION

This paper underscores the notable influence of human proximity on the evolution of antenna designs for mobile terminals, spanning generations from GSM to LTE, and from 5G to prospective technologies beyond. Our discourse provides a panorama of the prevailing challenges intrinsic to current antenna designs and articulates strategies to counteract the detriments of user-induced effects. For the task of radiation pattern classification with user effects, our models have achieved an impressive accuracy rate of up to 90%. Furthermore, when classifying the measured angular delay profile, we attained an accuracy of 87.5%. A limiting factor of our study is the scarce datasets for training our neural network, which partially caused over-fitting and narrow generalized application. Furthermore, if more diverse and rich data sets are acquired, the classification accuracy would be improved while adding more parameters to our AI classification algorithm, such as individual 5G mobile terminal antenna array elements. The proposed deep neural network not only signifies our advancements in AI-driven solutions, but also aligns with our overarching narrative of user effects on mobile antennas. These results, when viewed through the lens of our initial discussions on user effects, offer a timely perspective. Evidently, the evolution of antenna design, influenced by user interactions, has been paralleled by the realisation of our classification models.

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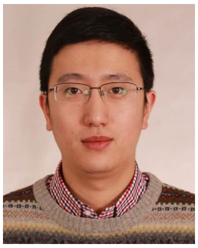

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