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***Abstract*—Mobile networks are rapidly expanding, and there is an increasing demand for seamless connectivity. Detecting whether a user is indoors or outdoors is pivotal in optimizing network performance and enhancing user experience. This paper proposes a semi-supervised learning method using a Long Short-Term Memory Autoencoder (LSTM-AE) that detects the user's environment. It uses mobile network radio signal data of real users. The LSTM Autoencoder learns to capture the underlying structure of the data and identify patterns that distinguish indoor from outdoor environments. Three key features are used to train the model: Reference Signal Received Power (RSRP), Channel Quality Indicator (CQI), and Timing Advance (TA). Results show that the LSTM-AE model achieves a high accuracy of 84% and an F1 score of 89%. In our approach, we achieve a substantial reduction of 34.14% in the requirement for labeled data compared to traditional methods that primarily rely on fully supervised learning. By diminishing the dependence on labour-intensive and time-consuming data labelling processes, this improvement significantly enhances the overall efficiency of the machine-learning process.**

***Index Terms*—LSTM, Autoencoder, LSTM-AE, anomaly detection, radio data, user environment**

I. Introduction

In today's fast-paced digital landscape, mobile networks have become the backbone of modern communication, enabling seamless connectivity and accessibility for millions of users worldwide. As reported in [1], there is a proliferation of smartphones and an increasing demand for high-quality services. This has led to the exponential growth of mobile network data, presenting a unique opportunity to extract valuable insights and optimize network performance. One critical aspect of mobile network optimization is accurately detecting and classifying user environments, such as distinguishing between indoor and outdoor settings [2], [3]. Understanding the user's environment is paramount for operators to make informed choices regarding resource allocation, coverage enhancement, user positioning or localization and quality of service/experience improvements. For example, in case of user positioning, location-based emergency services can use the information of user environment in addition to GPS location to quickly locate the users in need of assistance [4].

Supervised learning has been the conventional approach for environment detection, requiring manually labeled data. This process is, however, laborious specially when annotated manually by a group of annotators and impractical for large-scale or real-time applications. To tackle this problem, a semi-supervised learning approach using Autoencoder (AE) is proposed in this paper. Autoencoder is a class of neural networks which learns by encoding the input data into lower-dimensions and reconstructing it back to its original form [5]. Long Short-Term Memory Autoencoder (LSTM-AE) is a variant of traditional AE which is compatible for sequential data such as mobile network radio measurements collected over time. By exploiting the temporal time dependencies in the data, LSTM-AE can more accurately capture complex patterns and correlations, crucial for user environment detection. LSTM-AE has also shown good performance in detecting anomalies in an unsupervised manner [6].

A previous work [7] established that LSTM networks are effective for environmental detection. This work is extended here by introducing an semi-supervised LSTM-based model that does not require explicit labeled data yet maintains high accuracy. Our approach leverages anomaly detection techniques to identify outdoor environments as anomalous patterns within predominantly indoor settings. To evaluate our method's efficiency, we conducted extensive experiments on a real-world dataset of mobile network radio measurements, measuring the model's F1 score and accuracy. The results demonstrate the LSTM Autoencoder's effectiveness in accurately detecting user environments, showing promising performance compared to traditional supervised learning methods. By leveraging deep learning and LSTM Autoencoders, we provide a robust and efficient solution for semi-supervised user environment detection, empowering mobile network operators to enhance network performance, improve user experience, and facilitate a more connected future.

Given the limitations of supervised learning for environment detection, this paper explores a pivotal research question: "Can we reduce labeling in user environment detection and streamline anomaly detection process without compromising classification accuracy?". This question underpins our

investigation into LSTM-based model, leveraging LSTM Autoencoders for efficient and accurate user environment detection.

This paper is organized as follows. Section II presents some background and related work. Section III proposes our approach. Section IV discusses the results. The final section presents our conclusion.

II. Background and Related Work

The quest to discern mobile users' environment, distinguishing between indoor and outdoor or more specific environment like home, office, building, etc. has garnered extensive research interest in recent years. This is largely driven by the need to optimize network performance and enhance user experiences.

Anomalies are data points that do not conform to the expected behavior or do not fit well within the distribution of a dataset, and anomaly detection aims to identify infrequent patterns in data. Indoor environments are often the prefered or default place or more frequent user settings, especially in urban places [9]. Thus in the context of mobile networks, since most connected users are frequently indoors, user environment detection can be treated as an anomaly detection problem.

Detecting network anomalies is a broad research area, with significant research already put into it. Machine learning-centric approach to network anomaly detection explored various techniques such as such as Decision Trees, Support Vector Machines, Neural Networks, Random Forest, AdaBoost classifiers, etc., emphasizing their potential in identifying and addressing anomalies within network systems [10]–[14]. While these works provide a solid foundation, it does not focus on a practical implementation in dynamic, real-time scenarios. Furthermore, there remains a pressing need to explore and refine these methods within the specific context of mobile user environment detection, a domain with unique challenges and opportunities. Indoor environments can have complex signal patterns due to factors like walls, floors, and electronic devices, which can make indoor data more variable and harder to predict. These researches do not fully explore the intricate temporal dynamics of network data, a gap that LSTM models can fill [7]. According to [7], context-aware multi-task deep learning using LSTM are effective in capturing these complicated environment patterns and can handle the sequential nature of mobile network radio data. The methodology proves effective in discerning between different types of user settings and provides a good foundation. However, this approach relies heavily on labeled data for supervised training, which can be time-consuming and labor-intensive to produce.

This brings us back to the research question, "Can we reduce labeling in user environment detection and streamline anomaly detection process without compromising classification accuracy?". Building on this methodological advancements, our work aims to further advance this field by introducing a new learning approach using Autoencoders (AE). Autoencoder is a compelling unsupervised learning technique to diminish the reliance on extensive labeling, offering an innovative approach to understand and compress data without predefined labels [15]. Input data is encoded into a lower-dimensional representation, which is subsequently reconstructed to original form. Autoencoders are used for dimensionality reduction, anomaly detection or feature learning. It is well-suited for anomaly detection because they learn to reconstruct normal data well, but struggle to reconstruct anomalies.

LSTM Autoencoder combines the strengths of LSTM and AE, capturing temporal dependencies in data while performing unsupervised learning. One of the key advantages of using LSTM Autoencoder is the ability to effectively learn the feature representations from data without requiring explicit labels. Previous research in [6] explores Long Short-Term Memory Autoencoder (LSTM-AE) in softwarized network infrastructures, particularly radiography. However, the scope of [6] is limited to specific types of anomalies, not covering mobile user environment detection context.

To the best of our knowledge, our paper is the first to explore the application of LSTM-AE to mobile network data for semi-supervised user environment recognition. It significantly reduces the dependency on labeled data, addressing the challenges of manual data labeling and offering adaptability to different network scenarios.

III. LSTM Autoencoders for User Environment Sensing

This section outlines our approach on leveraging LSTM Autoencoders (LSTM-AE) for Indoor-Outdoor Detection (IOD) using unlabelled radio signal data which is easily acquirable in distributed mobile networks.

A. Data Description

In this study, we leverage a refined dataset, previously utilized in the work [7], [8]. There are 104202 Indoor and 35576 Outdoor datapoints. Data collection occurred across varied settings, including homes, outdoors, transportation etc., at different times of the day. This passive approach ensures the dataset closely mirrors genuine user behavior and real-world environments. In our dataset there were already several indoor environments like different types of buildings, home, mall and office. Fig. 1 depicts RSRP data variation across different environments. We observe also that RSRP values vary less when user is indoor, while they vary much more when user is outdoor. When user is outdoor and moving then the multiple paths of radio propagation can change, causing the phenomenon known as multi-path induced fading creating constructive or destructive interference as user is moving. In comparison, in indoor places, the users are relatively less mobile.

The focus was on the following three key mobile network features:

- RSRP (Reference Signal Received Power): Measures the average received power of a single reference signal resource element.

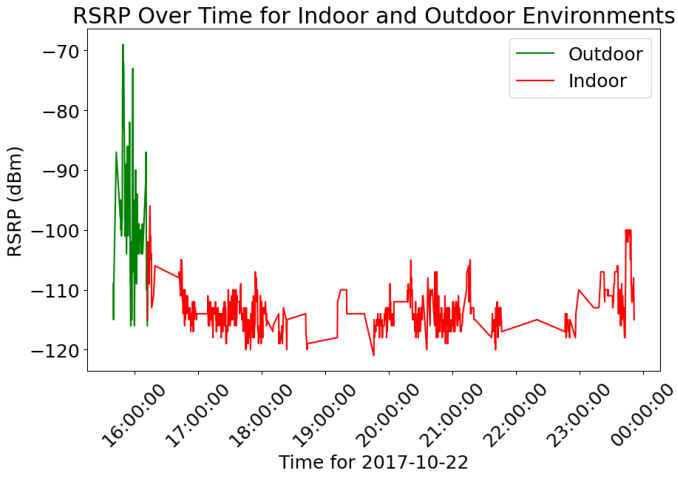

Fig. 1. RSRP variations on a sample of the database

- CQI (Channel Quality Indicator): reported by UE to BS, it gives the most appropriate modulation scheme and coding scheme to be used for transmission.
- TA (Timing Advance): Controls signal transmission timing.

These radio features contain valuable information about the user's proximity to the network base stations and the signal strength experienced by the user's device. These three mobile network features were chosen because of their demonstrated effectiveness in environment detection tasks, as shown in the foundational paper [8]. Minimal preprocessing was needed due to the data-set's well-structured nature, allowing for a direct and efficient analysis. The LSTM Autoencoder is trained on this dataset, featuring diverse user mobility patterns and signal measurements, to effectively distinguish between indoor and outdoor environments.

Collecting network traffic for users on the network is a requirement for this project to provide accurate results. It is worth noting that the data used in this research contains no personally identifiable information, and is only used to train our model.

B. LSTM-AE Model for IOD

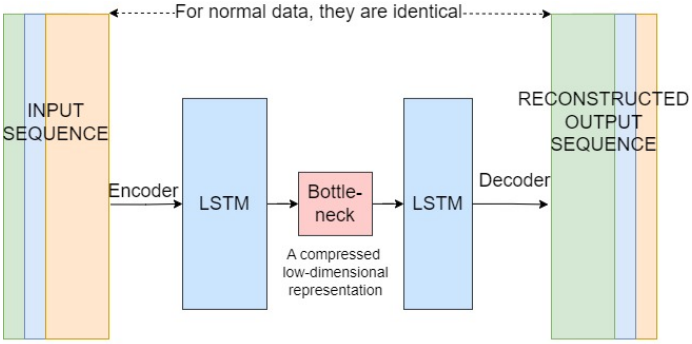

Fig. 2. Illustration of LSTM-AE model architecture

As seen in Fig 2, the core of our LSTM-AE model comprises of two main components: the Encoder and the Decoder. The Encoder's role is to efficiently compress input features, processing them through two layers of LSTM networks, thereby reducing the data to a manageable latent space. Initially, it transforms the tensor with three input features into a 256-dimensional state, which is then further condenses this state into a 128-dimensional space. Conversely, the Decoder tries to reconstruct the original input from the compressed data, utilizing another two LSTM layers followed by a dense layer. This dense layer is pivotal in translating the 128-dimensional latent representation back into the original three-feature variable space, ensuring a proper reconstruction of the input. This architecture not only underscores the model's capability to handle and analyze sequential data effectively but also illustrates our approach on avoiding explicit labelling in the context of mobile network analysis. This model is implemented using the PyTorch framework, chosen for its flexibility and dynamic computation graph, which is more apt for this specific application. The experiment is run on NVIDIA T4 GPU with 15 GB GPU RAM, a standard CPU, and 12 GB system RAM. The setup enables efficient training and testing of the LSTM Autoencoder model on a large dataset.

C. Efficient data utilisation

Our LSTM Autoencoders (LSTM-AE) model is used to differentiate between indoor and outdoor environments by considering the prevalent indoor data as the baseline 'normal' state. Given the background understanding that indoor environments are more common [9], our model treats the less frequent outdoor data as anomalies. Therefore, our model treats indoor data as normal, and the minority outdoor data as anomaly. This strategic decision allows us to capitalize on the autoencoder's strength in detecting anomalies, enhancing the model's ability to accurately discern user's environment within mobile networks.

The LSTM Autoencoder is thus trained exclusively on indoor data to establish a baseline for 'normal' conditions and construct a detailed internal representation of indoor environment. The outdoor data, which is not seen during training, is presented to the model during the testing phases. Thus, the outdoor data is used to test and evaluate the model's ability to effectively differentiate the outdoor environments based on the model's learned indoor norm. There are no explicit labels in the training dataset and during the validation and testing phase. In contrast, conventional methods entail sending all data, including outdoor and indoor data, to a central location. Subsequently, the training process is carried out on the entire dataset.

To estimate our savings, we consider the data that remains unsent and unused for training in our approach:

$$savings \approx \frac{Data_{outdoor}}{Data_{total}} \tag{1}$$

This gives us a savings of 34.14%. From the total indoor data available, 85% of the indoor data is used for training

the model, 10% of indoor data is used for validation to fine-tune model parameters, and remaining 5% was reserved for testing the model's capability to generalize. Thus, outdoor data and labels, which represents 34.14% of the whole data, is not involved in this training process.

D. Analysis of Reconstruction Errors while using LSTM-AE

In LSTM-AE models trained on indoor data, the Mean Squared Error (MSE) loss function is used to quantify the difference between original and reconstructed data. MSE loss performed better than l_1 loss function for this model, as MSE loss function is ideal for capturing small nuances between the reconstructed and original data, thereby aiding in more accurate user environment detection. Since the model is trained predominantly on indoor data, the model learnt the patterns and nuances of indoor environments very well. Consequently, when evaluating indoor data (considered 'normal' in this context) the reconstruction error (MSE) is typically low because the model can accurately predict indoor environment patterns. Conversely, outdoor data points which the model sees as 'anomalous' because it wasn't trained on it, results in higher MSE values due to the model's inability to accurately reconstruct these unseen patterns. This discrepancy in MSE error rate values allows the model to distinguish between indoor and outdoor environments effectively similar to a binary classifier.

To effectively classify environments using LSTM Autoencoder models, setting an MSE error loss threshold is crucial to distinguish between indoor (low MSE rate) and outdoor (high MSE rate) environments. By establishing a threshold value, the model simplifies environmental classification into a binary decision-making process. When the reconstruction loss is below this threshold, the environment is considered 'normal' (indoor), indicating a close match between the reconstructed and original data. Conversely, losses exceeding the threshold signify 'anomalous' (outdoor) environments, where the model's predictions diverge significantly from the actual data. This strategy facilitates accurate, and real-time differentiation between indoor and outdoor settings, enhancing the model's practical utility for user environment detection.

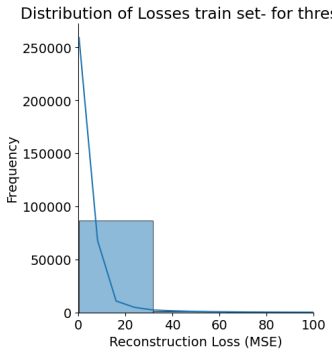

Fig. 3. Distribution of training set losses used for determining threshold for model

Fig 3 shows the distribution of reconstruction losses (MSE) for training dataset versus the threshold. The X-axis represents the reconstruction loss value ranges and Y-axis shows how the number of data points are distributed vs. MSE values. Only indoor dataset is shown to the model for train. This distribution is used to set an appropriate threshold for IOD.

The objective in selecting a MSE threshold here is to minimize the classification problem as much as possible. This MSE threshold will later be used for classification: patterns showing lower MSE than threshold will be classified as indoor and vice-versa for outdoor. This choice is crucial because during training, the model learns to reconstruct seen patterns with low MSE, while patterns different from the seen patterns have higher MSE. However, setting the threshold too low risks incorrect classification of indoor points. For instance, in Figure 3, we observe that over 50,000 indoor points have an MSE exceeding 10. To strike a balance between sensitivity and specificity, we opt for a threshold of 25. This threshold value effectively filters out only a minimal number of normal indoor points while still being able to classify outdoor points. Values below 25 suggest an indoor environment ('normal'). Conversely, MSE values above 25 indicate an outdoor environment ('anomalous'), where the model encounters higher errors due to unfamiliar anomalous data patterns. This threshold-based approach enables quick, precise and efficient environment classification.

IV. Results and Discussion

This section delves into the evaluation of the LSTM Autoencoder model's IOD performance on the test data. Utilizing a dataset previously explored, the model's effectiveness is quantitatively assessed through F1 score and accuracy metrics. The F1 score (equation 2) provides a balanced measure of the model's Precision and Recall, and Accuracy (equation 3) offers a straightforward assessment of its overall classification success.

$$\text{F1-score} = 2\frac{Precision.Recall}{Precision+Recall} \tag{2}$$

$$\text{Accuracy} = \frac{\text{True Positives+True Negatives}}{\text{Total number of data points}} \tag{3}$$

These measures highlight the model's potential for real-world application.

TABLE I
Performance metrics of the model on test data

Epoch(s)	F1 score (%)	Accuracy (%)	Precision (%)	Recall (%)	Training Time (min)
Our approach: LSTM Autoencoder					
1	80	70	98	68	6
3	90	82	92	88	18
10	89	84	91	87	63
SOA approach: Fully Supervised LSTM [16]					
10	94	94	94	94	1.3

Table I shows the performance metrics improvement during our model's training phase. Our experiments' choice of epoch numbers was based on balancing computational resources with

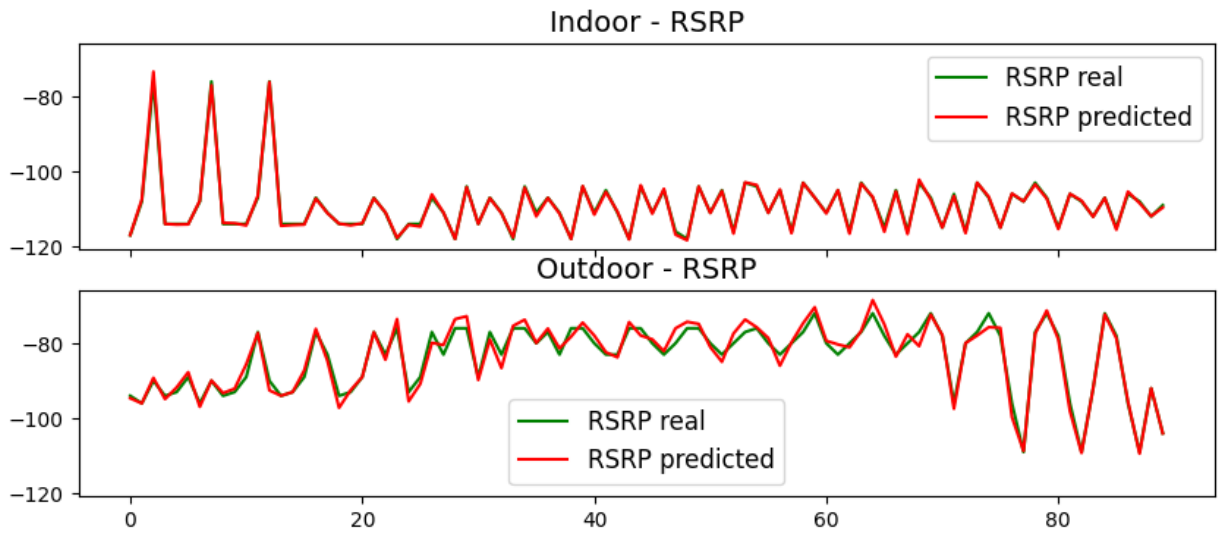

Fig. 4. Overlay the real and reconstructed Time Series values for RSRP feature, for normal (indoor) and anomaly (outdoor) environments

performance gains. Preliminary tests indicated that increasing the number of epochs beyond the selected numbers did not bring out significant performance improvements. Thus, we focused on optimizing model performance within a reasonable training time, which proved effective for our application. Our LSTM Autoencoder model achieved a promising F1 score of 89% and Accuracy of 84%, thus validating our approach. Given the complexity of the dataset, the model performed exceptionally well in our evaluations. The metrics suggest that our LSTM Autoencoder model is highly effective in distinguishing between indoor and outdoor user environments. The performance of the model indicate its robustness and reliability in classifying user environments in mobile networks. By employing this approach, we have significantly reduced the cost associated with data labeling, making this a scalable solution for larger datasets. The user environment is dynamic (buildings, home, mall, office etc.) and evolves with respect to the user mobility. Consequently, there might be a need to regularly retrain the model again using new data. Our model in such cases provides a low cost solution for an efficient detection of the dynamic environment.

In comparison, a fully supervised method based on LSTM [16] achieved a F1-score of 94%. For a supervised LSTM method, both the indoor and outdoor data is used to train model. Besides, it requires labelling both indoor and outdoor data, making data collection more challenging as compared to our approach. In our approach, using only indoor data in an unsupervised way avoids use of outdoor data and also avoids explicit indoor and outdoor labels.

To accelerate the training process of our LSTM Autoencoder model, we utilized Graphical Processing Unit (GPU) resources. The parallel processing capabilities of GPUs allowed to handle the computationally intensive tasks associated with deep learning more efficiently. This not only significantly reduced the training time but also enabled experimentation with larger datasets and more complex models, improving the overall performance and accuracy of our environment detection system. Our model took approximately 1 hour to complete 10 epochs, demonstrating reasonable computational efficiency given the complexity of the architecture and the size of the dataset.

In our model, we observed a trade-off between accuracy and the F1 score when setting the anomaly threshold. After numerous trials, a Mean Squared Error (MSE) value of 25 was selected as the suitable threshold for distinguishing anomalies, which in this context refers to user environments. The nuanced calibration of this threshold value should be based on the type of errors the network providers can tolerate. There is a delicate balance between false positives (outdoor environment considered as anomalies) and false negatives (anomalies considered as outdoor), which needs to be established by lowering or increasing the threshold value respectively. This is essential for optimizing the model's practical utility in real-world scenarios.

In addition to the loss and accuracy metrics previously discussed, Figure 4 offers a visual comparison of the model's performance by comparing the real versus the predicted time series values for the RSRP feature for test data. The real values are depicted by a green line, while the model's predictions are overlaid in red. For instances classified as 'normal (indoor)', the overlapping of the two lines is so complete that the green line is virtually obscured by the red, indicating an almost perfect reconstruction. This close correspondence suggests that when the LSTM Autoencoder is presented with data resembling the training set (indoor scenarios), it can accurately reconstruct the sequence, confirming the model's precision in familiar indoor contexts. Conversely, for 'anomaly' (outdoor) instances, there is a noticeable difference between the real and predicted values. The deviation aligns with expectations for user environment detection. As the model was trained

on indoor data, outdoor environments are expected to be more challenging to reconstruct. This visual evidence between normal and anomaly behaviour complements our quantitative evaluations, reinforcing the model's utility in both feature learning and anomaly detection for Indoor-Outdoor Detection.

V. Conclusion

In conclusion, our study proposes a novel application of LSTM Autoencoders for user environment detection in mobile networks, showcasing a promising semi-supervised learning approach. While the previous work presented in [7] concluded that LSTMs are best suited for this task, our model takes it a step further by introducing LSTM-AEs, reducing the need for expensive labeling and making the process more efficient. We achieved a 34.14% reduction in data labeling requirements through our approach. By leveraging unlabelled data, we demonstrate the model's capability to accurately differentiate between indoor and outdoor environments, as evidenced by robust F1 scores and accuracy metrics.

The strategic implementation of MSE loss thresholds further refines the model's anomaly detection efficiency. This research not only contributes to the field of mobile network analysis but also paves the way for future advancements in unsupervised learning models for environmental detection. The LSTM Autoencoder model demonstrates encouraging results and warrants further research and model refinement. Our findings suggest significant potential for reducing the reliance on labeled data, offering scalable solutions for complex datasets in real-world applications.

In future, we would like to do more in-depth quantitative evaluation using metrics like Mean Squared Error (MSE) or Mean Absolute Error (MAE) to better understand the model's limitations. Future work could focus on optimizing the model architecture and testing this model on several data-sets having different types of network data.Further, indoor data may evolve as network infrastructure improves and signal measurements become more accurate or granular, which could necessitate retraining the model to adapt to the new data patterns and ensure continued accuracy in detecting user environments.

References

[1] "Smartphone Users Worldwide 2014–2020," Statista. [Online]. Available: https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/. [Accessed: Nov. 7, 2018].

[2] N. D. Lane et al., "A survey of mobile phone sensing," in IEEE Communications Magazine, vol. 48, no. 9, pp. 140-150, Sept. 2010, doi: 10.1109/MCOM.2010.5560598.

[3] A. Esmaeili Kelishomi et al., "Mobile User Indoor-Outdoor Detection through Physical Daily Activities," Sensors, vol. 19, no. 3, Art. no. 511, 2019, https://doi.org/10.3390/s19030511.

[4] "Technical Specification Group Services and System Aspects; 5G System (5GS) Location Services (LCS); Stage 2 (Release 18) .

[5] U. Michelucci, "An introduction to autoencoders," arXiv preprint arXiv:2201.03898, 2022.

[6] Alessio Diamanti, José Manuel Sanchez Vilchez, Stefano Secci. LSTM-based radiography for anomaly detection in softwarized infrastructures. International Teletraffic Congress, IEEE, Sep 2020, Osaka, Japan. 10.1109/ITC3249928.2020.00012. hal-02917660

[7] S. A. Hamideche, M.-L. A. Morel, K. Singh, and C. Viho, "Indoor-Outdoor Detection using Time Series Classification and User Behavioral Cognition," in *WMNC 2022 14th IFIP Wireless and Mobile Networking Conference*, Sousse, Tunisia, Oct. 2022, pp. 1-8, doi: 10.23919/WMNC56391.2022.9954290. HAL Id: hal-03830890. [Online]. Available: https://hal.science/hal-03830890.

[8] Marie Line Alberi Morel, Illyyne Saffar, Kamal Singh, Sid Ali Hamideche, César Viho. "Improving User Environment Detection Using Context-aware Multi-Task Deep Learning in Mobile Networks", IEEE Transactions on Cognitive Communications and Networking, 2022, pp.1-11.10.1109/TCCN.2022.3205696. hal-03781983

[9] I. Saffar, M. L. Alberi Morel, M. Amara, K. D. Singh, and C. Viho, "Mobile User Environment Detection using Deep Learning based Multi-Output Classification," in *Proc. 2019 12th IFIP Wireless and Mobile Networking Conference (WMNC)*, Paris, France, 2019, pp. 16-23, doi: 10.23919/WMNC.2019.8881474.

[10] T. Ahmed, B. Oreshkin, and M. Coates, "Machine learning approaches to network anomaly detection," in Proceedings of the 2nd USENIX Workshop on Tackling Computer Systems Problems with Machine Learning Techniques, April 2007, pp. 1-6.

[11] W. Wang, Q. Chang, Q. Li, Z. Shi, and W. Chen, "Indoor-Outdoor Detection Using a Smart Phone Sensor," Sensors, vol. 16, no. 10, p. 1563, Sep. 2016, doi: 10.3390/s16101563.

[12] A. Esmaeili Kelishomi, A. H. S. Garmabaki, M. Bahaghighat, and J. Dong, "Mobile User Indoor-Outdoor Detection Through Physical Daily Activities," Sensors, vol. 19, no. 3, p. 511, Jan. 2019, doi: 10.3390/s19030511.

[13] M. Markou and S. Singh, "Novelty detection: a review—part 1: statistical approaches," in Signal Processing, vol. 83, no. 12, pp. 2481-2497, 2003, doi: 10.1016/j.sigpro.2003.07.018.

[14] M. Markou and S. Singh, "Novelty detection: a review—part 2: neural network based approaches," in Signal Processing, vol. 83, no. 12, pp. 2499-2521, 2003, doi: 10.1016/j.sigpro.2003.07.019.

[15] Goodfellow, I., Bengio, Y., Courville, A., Bengio, Y. (2016). Deep learning (Vol. 1). Cambridge: MIT press

[16] Hamideche, S. A., Morel, M. L. A., Singh, K., Viho, C. (2022, October). Indoor-outdoor detection using time series classification and user behavioral cognition. In 2022 14th IFIP Wireless and Mobile Networking Conference (WMNC) (pp. 7-14). IEEE.