Received 28 February 2024, accepted 20 March 2024, date of publication 27 March 2024, date of current version 2 April 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3382135

RESEARCH ARTICLE

Indoor Localization With an Autoencoder-Based Convolutional Neural Network

HATICE ARSLANTAS[1] AND SELCUK OKDEM[2]
[1]Department of Computer Engineering, Erzincan Binali Yildirim University, 24100 Erzincan, Turkey
[2]Department of Computer Engineering, Erciyes University, 38030 Kayseri, Turkey

Corresponding author: Hatice Arslantas (hatice.arslantas@erzincan.edu.tr)

ABSTRACT Nowadays, studies on indoor localization systems based on wireless systems are increasing widely. Indoor localization is the process of determining the location of objects or people inside a building. Global Navigation Satellite System (GPS) signals do not provide sufficient location data indoors because they are interrupted or completely lost in closed areas. For this reason, studies on indoor localization system design with machine learning and deep learning techniques based on Wi-Fi technology are increasing. In this study, we propose a method and training strategy that is entirely based on a Convolutional Neural Network (CNN) and a combined autoencoder that automatically extracts features from Wi-Fi fingerprint samples. In this model, we coupled an autoencoder and a CNN and we trained them simultaneously. Thus, we guarantee that the encoder and the CNN are trained simultaneously. The proposed system was evaluated on the UJIIndoorLoc and Tampere datasets. The experimental results show that the proposed model performs significantly better than the current state-of-the-art methods in terms of location coordinates (x, y) localization. In our study, runtime analysis is also presented to show the real-time performance of the network we proposed.

INDEX TERMS Indoor localization, Wi-Fi fingerprint localization, convolutional neural network, autoencoder.

I. INTRODUCTION

Nowadays, studies on indoor location-based systems are in significant demand. Indoor location-based services offer applications in various areas such as security and monitoring. Accurately detecting the user's location in closed situations can sometimes be vital. Indoor localization systems help by reducing time loss in reaching users in emergencies. Outdoor localization systems based on the Global Navigation Satellite System (GPS) do not provide successful results in indoor localization due to limited signal transmission. Numerous approaches for indoor localization systems have been proposed to address these limitations. It works on technologies such as Wi-Fi, Bluetooth, and Radio Frequency Identification for indoor localization services. For indoor localization, Wi-Fi technology is preferred due to its widespread use, low cost, and wide accessibility.

The associate editor coordinating the review of this manuscript and approving it for publication was Hang Shen.

Various signal measurements used in Wi-Fi-based indoor localization include received signal strength (RSSI), time of arrival (TOA), time difference of arrival (TDOA), and round trip time (RTT). They are wireless technologies that provide location estimation by measuring different parameters such as round trip time, angle of arrival (AOA), and Channel State

Information (CSI). Among these measurements, RSSI is the more frequently preferred method in indoor localization systems. In addition, the use of RSSI technology also has difficulties such as signal variability, noise, and accuracy problems.

Fingerprint-based methods are methods used to find the location of a device or user in complex indoor localization systems. The fingerprint-based method consists of two stages: in the offline stage, a signal map is created with the signal strengths received from reference points. In the online phase, it collects signal strengths from access points around the user in an unknown location and sends them to the server that has the signal map. The server estimates the user's location by comparing and analyzing the user's signal strength vector with the fingerprints of reference points [1]. The main challenge in Wi-Fi fingerprint-based indoor localization is calculating the estimations with high accuracy and low cost. Many solutions of varying complexity have been proposed for the indoor localization problem. In addition, the indoor localization problem is solved by classifying which floor or building the user is on or estimating the user's location in some coordinate system. In this context, the problem is that the same network achieves high accuracy with low complexity and low computational cost for both classification and regression subproblems. Therefore, in our study, a convolutional neural network with an autoencoder feature enhancer that solves all these problems is proposed.

Neural networks provide high accuracy and performance in indoor localization applications due to their ability to adapt to complex data structures and model nonlinear relationships. In this study, floor classification and location regression experiments were conducted on the UJIIndoorLoc [2] dataset, and location regression experiments were conducted on the Tampere [3] dataset using a convolutional neural network model with an autoencoder.

The main contributions of our proposed framework are as follows:

1. Unlike most of the other studies, our proposed model is solely based on convolutional networks. When compared to other studies that use sequential models, the use of convolutional neural networks reduces unnecessary complexity. As a result, our proposed model achieved high success with minimal computational cost.
2. Due to the sparse nature of fingerprint data, it has been observed that training the fingerprint data directly with a convolutional neural network reduces the overall floor hit rate accuracy. It is known that the autoencoder structure is frequently used to reduce the size of the data and to map the data into a more separable space. In our study, instead of using a pre-trained autoencoder directly, the approach of training this structure simultaneously with a convolutional neural network is proposed. Thus, the two networks were able to improve each other's training process by transferring information between each other. For this purpose, a combined loss function was defined and used.
3. Some other studies have proposed separate models for classification and location estimation. With the model proposed in our study, both floor classification and Cartesian location estimation were made.
4. One of the other contributions of our study is a runtime analysis to show the real-time operability of the proposed method. As a result, it has been shown that the method works on GPU with a very small time cost.

This paper is organized as follows: Section II provides a review of some indoor localization related works. Section III describes the dataset used in this study and the proposed model. Section IV presents experimental results using the UJIIndoorLoc and Tampere datasets. Finally, our study was concluded in the conclusion section.

II. RELATED WORKS

In recent years, many approaches have been proposed for indoor localization systems. Technologies such as Wi-Fi, Bluetooth, magnetic field sensors, and UWB (Ultra-Wide Band) are among the popular solutions for indoor location detection. Various classification and regression algorithms have been used in the literature for indoor localization with Wi-Fi existing infrastructure.

Jang et al. proposed localization with a CNN-based Wi-Fi fingerprint method [4]. In this proposed method, they achieved a high accuracy classification by combining building and floor labels. Alitaleshi et al. [5] proposed a new solution by combining an autoencoder (ELM-AE) and a two-dimensional CNN model. They performed feature extraction by reducing the input size with an autoencoder. They also evaluated the localization performance with CNN. Additionally, to increase the floor hit rate accuracy, they augmented the data by adding noisy data to the original fingerprint map. It is seen that the floor accuracy rate also increases with the increasing data set. Ahmed Elesavi and Kim proposed a method based on a recurrent neural network (RNN) that sequentially estimates coordinates from a building to find the target location [6]. Nowicki M. and Wietrzykowski J. apply a deep learning technique to implement a Stacked Autoencoder (SAE) and multiclass classifier. Their proposed model was trained as one of the labels of combined building and floor identifiers [7]. In addition, Sinha and Hwang proposed only a single localization model using CNN [8].

Incorporating deep learning techniques into indoor localization offers a promising solution to address the limitations of fingerprint-based localization. Currently, researchers are actively applying deep learning approaches to enhance indoor localization accuracy. For example, [9] and [10] used a DNN for indoor visual localization.

This study [11], proposes a new indoor localization model using a convolutional neural network-based fingerprint technology to solve the indoor localization problem. The goal is to improve Wi-Fi indoor localization by optimizing the data collection process. There are also indoor location estimation system studies in the literature [12], [13], and [14].

Song et al. performed floor classification and positioning error on the UJIIndoorLoc dataset by reducing the dimensionality with the stacked autoencoder [15]. To tackle the multi-floor identification problem, Zhao et al. [16] proposed a Gradient Boosting Neural network based model. Their proposed indoor localization model has high floor hit rate accuracy. [17] developed a model based on the Wi-Fi Autonomous Block Model for large buildings. Jia et al. [18] developed an algorithm based on Long Short-Term Memory Network (LSTM). In the case of a limited number of collected reference points in this study, principal component analysis was used to select the access point, and Gaussian process regression was used to model the reference point coordinates and the corresponding received signal strength values in the training sample set. Kim et al. [19] proposed an SAE based deep neural networks (DNN) architecture. Bellavista- Parent, Torres-Sospedra, and Pérez-Navarro conducted a comprehensive research of the studies carried out with machine learning methods in Wi-Fi-based indoor positioning [20]. Ayınla et al. proposed a method based on SAE and LSTM framework in WiFi fingerprint-based indoor localization. This method uses SAE to reduce the dimensions of RSSI samples, while ALSTM is trained to estimate indoor location by focusing on these features. The proposed method was evaluated with UJIIndoorloc, Tampere and UTSIndoorLoc datasets [21].

While autoencoders are trained independently of CNN in similar studies in the literature, in this study the encoder was trained simultaneously with CNN. We think that this approach gives more successful results because the networks are optimized by connecting them. The proposed model and certain deep learning-based localization methods are mentioned in Table 1.

TABLE 1. Different indoor localization studies in the literature.

Ref.	Datasets	Technology	Method	Loss Function
[4]	UJIIndoorLoc dataset	Wi-Fi APs	CNN	Not mentioned in the article
[5]	UJIIndoorLoc dataset Tampere dataset	Wi-Fi APs	AE and CNN	Mean Squared Error (MSE) and Cross-entropy
[6]	UJIIndoorLoc dataset	Wi-Fi APs	RNN and SAE	MSE
[7]	UJIIndoorLoc dataset	Wi-Fi APs	SAE	Not mentioned in the article
[15]	UJIIndoorLoc dataset Tampere dataset	Wi-Fi APs	SAE and CNN	(MSE)
[19]	UJIIndoorLoc dataset	Wi-Fi APs	SAE and DNN	Binary Crossentropy
[21]	UJIIndoorLoc and Tampere dataset	Wi-Fi APs	SAE and ALSTM	MSE
Our Study	UJIIndoorLoc dataset Tampere dataset	Wi-Fi APs	AE and CNN	$\mathcal{L}_{\mathrm{AE}} + \mathcal{L}_{\mathrm{CNN}}$

III. MATERIALS AND METHODS

This section describes the parts of the proposed localization architecture. Details of the dataset and model used in the method are explained respectively. The proposed system architecture is shown in Fig. 1. During the offline phase, Wi-Fi fingerprints are gathered from training reference points to construct the offline radio map. Subsequently, after completing the training, the Autoencoder-based CNN proposed in this study will be deployed for real-time localization. In the online phase, the pre-processed RSSI vector collected from the user's device is input into the model to predict the target location.

A. DATASET DESCRIPTION

Two different datasets are used for evaluating the performance of our proposed model.

The UJIIndoorLoc dataset is a public dataset that contains Wi-Fi fingerprint and location data collected in a multi-story university building. The dataset has been used in many studies on indoor localization. Experimental studies of the proposed model were carried out using a multi-building and multi-floor dataset, the UJIIndoorLoc dataset, which can be downloaded from the accessible UCI Machine Learning Repository. This dataset covers three-four- or five-floor buildings within the Universitat Jaume I University campus. It consists of 19937 and 1111 samples collected from a total of 520 access points (AP). The data has 529 attributes. The first 520 attributes provide information about RSS from these APs and contain values ranging from -104 dBm to 0 dBm. The other parameters are longitude and latitude of measurement, floor ID, building ID, space ID, relative position, user ID, phone ID, and the timestamp of the measurement. The dataset includes training and validation data. All studies use validation data as test data. In this study, the validation data of the UJI dataset was used as a test.

The second dataset utilized in this study is the Tampere dataset, which comprises 4,648 fingerprints meticulously gathered from 992 Wireless Access Points (WAPs) spanning across a five-floor edifice situated at the Tampere University of Technology. Within the scope of this review, all 697 training fingerprints were meticulously utilized for the training phase. Additionally, a curated subset comprising a total of 3,951 fingerprints was earmarked for utilization as the test dataset. This ensures a comprehensive evaluation of the proposed methodologies, thereby enhancing the robustness and reliability of the findings obtained.

Data preprocessing is one of the basic steps before applying deep learning algorithms. As part of preprocessing, the values of the input raw RSS in the dataset range from -110 dBm to 100 dBm. And then normalized the RSS data in the dataset with equation (1) [0 1] values. x_{min}, x_{max} represent the minimum and maximum RSS values.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

B. AUTOENCODER BASED CNN CLASSIFICATION

CNN plays a crucial role in Wi-Fi fingerprint localization classification. In this study, an autoencoder-based CNN classifier model is proposed. To address the challenge of too many zero values in the original data, which hindered the performance of CNN filters, we aimed to enhance data

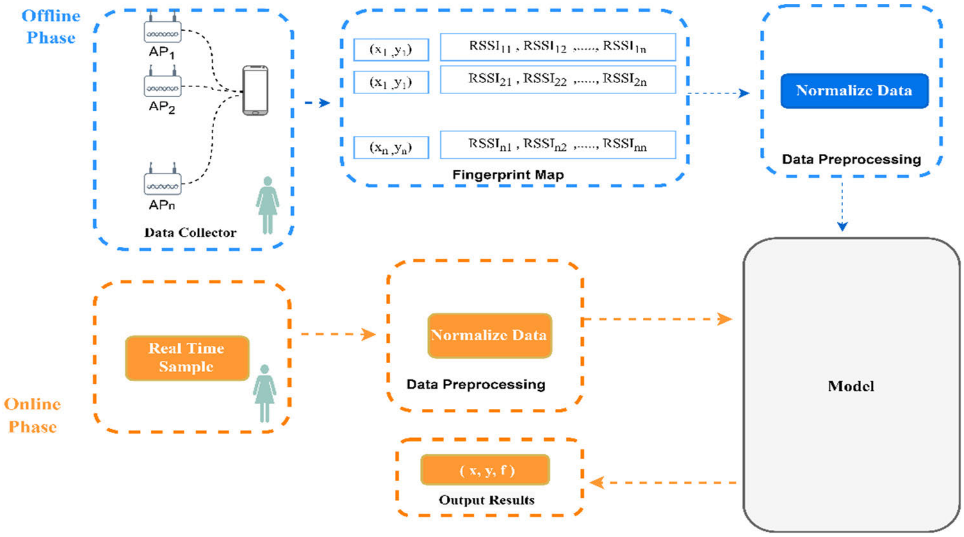


FIGURE 1. System architecture.

quantity and processability by providing normalized data to the autoencoder. The design intent of the network is to transform the data into a different dimension using the autoencoder and extract more meaningful features that we believe better represent the data. We think these new features better represent the same data. We set the size of the created image tensor to be square for easy design of the CNN architecture. Fig.2 shows the architecture of the proposed model for indoor localization. The proposed model is a method that is an autoencoder-based CNN classifier and regression model. With the encoder, 520 inputs are increased to 1600, then this data is converted into a 40×40 image-like tensor and given as input to the CNN classifier.

The training process involved combining Autoencoder and CNN losses. While the autoencoder used Mean Squared Error (MSE) loss, Loglikelihood was used as the loss function for the classifier, and MSE was used for x, y localization. These two losses were combined during training, with the initial loss calculated using the MSE metric between the input and predicted output of the Autoencoder. We think that training the networks by connecting them optimizes both the autoencoder and CNN parts to give more successful results. This is an important contribution to our study.

To classify floors using the CNN model, the FloorID tag was used to identify 5 separate floors in the entire target area. The proposed CNN model consists of four convolution layers. The convolution layers with 32,64,128,256 layers in

the model. We used a 3×3 filter and stride value of 2 for the convolution operations. The activation function used in the hidden layers are the LeakyReLU function. The LogSoftmax activation function is used in the output layer.

The same CNN model was used to estimate the x,y regression. The only difference here is the output layer activation function. The Tanh activation function is used in the output layer. The model was trained with the UJIIndoorLoc train set and tested with the validation set. The optimal learning rate value was discovered by experimenting with various learning rate values throughout the training to properly train the network and get the best results. The most optimum result was obtained by reducing the learning rate in certain epochs. A scheduler was used to automatically change these values. During the training phase, various optimizers were studied and the optimizer that gave the most successful results was selected. Using the early stopping strategy, the training was stopped at the place where we achieved the most successful results. The method we propose not only improves performance with five parameters but also adds speed and real-time operability. Table 2 shows the proposed model parameters.

TABLE 2. Proposed model parameters.

Parameters	Value
Max Epoch	175
Batch Size	128
AE Hidden Layers	2048, 1600, 2048
AE Activation Layers	Tanh
AE Optimizer	Adam
AE Loss	Mean Squared Error (MSE)
CNN Activation Layers	LeakyReLU
CNN Optimizer	Adam
Loss function	$\mathcal{L}_{AE} + \mathcal{L}_{CNN}$
Initial Learning rate	2e-6
Classfier / Regressor Output Layers	LogSoftmax / Tanh
Schedular step_size	20

IV. EXPERIMENTAL RESULTS

In this section, the prediction floor hit rate accuracy of the trained networks, the loss graph of the model, and

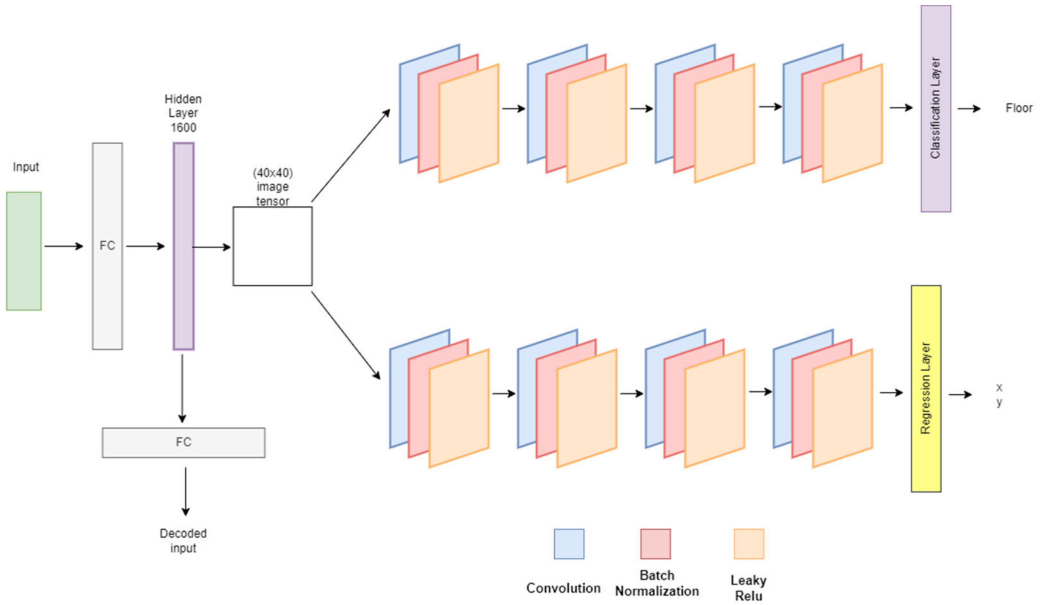


FIGURE 2. Autoencoder based CNN model for classification and regression.

performance measurements are shown to demonstrate the capabilities of the model.

	precision	recall	f1-score	support
0	0.90	0.92	0.91	132
1	0.95	0.97	0.96	462
2	0.98	0.95	0.96	306
3	0.98	0.98	0.98	172
4	0.97	0.92	0.95	39
accuracy			0.96	1111
macro avg	0.96	0.95	0.95	1111
weighted avg	0.96	0.96	0.96	1111

FIGURE 3. UJIIndoorLoc dataset floor predict classification report.

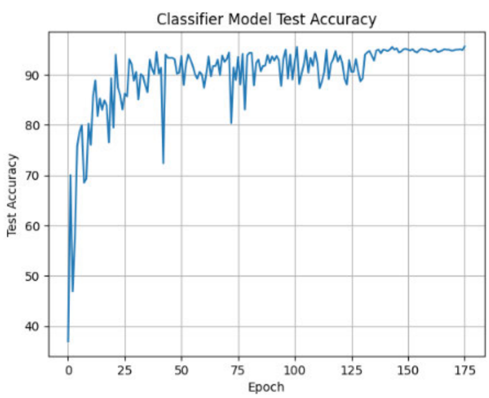


FIGURE 4. UJIIndoorLoc dataset classifier model test floor hit rate accuracy.

A. EVALUATION OF THE PROPOSED MODEL

In this section, we provide the localization results of the proposed method on the UJIIndoorLoc validation dataset and the Tampere test dataset. After the pre-processing which is described in the section ''Dataset Description'', the proposed model was trained and tested. As a result of the experiments, the classification floor hit rate accuracy was 95.58% and the minimum error in x y localization was 4.55 m. To show the floor hit rate accuracy and loss performances of the classifier model over 200 epochs Fig. 4 and 5 are presented. The loss figure contains results from both training and validation datasets. It was observed that the validation loss value was higher than the training loss value until the 140th epoch and became close to each other after this epoch. When the graphs are examined, the loss value of the model proposed for the data set decreases, and the floor hit rate accuracy values of the model increase as the number of periods increases. Figs. 4 and 5 show that there was no overfitting situation in the 200 epochs. Fig.6. show the loss of the proposed regression method for the dataset with 200 epochs of training and validation sets. As shown in Table 3 and Table 4 we compared our proposed model with five CNN models in the literature and achieved higher performance than those reported in the literature. It shows that the proposed method achieves better accuracy in floor hit rate and mean localization error.

The classification report obtained by training the model is shown in Fig. 3. This figure shows the precision, recall, and f1 score results for five-floor identification. Precision measures how many of the samples the model predicts as positive are positive. Recall measures how many of the truly positive examples were correctly predicted by the model. F1-score is a metric that evaluates the performance of a classification model by combining precision and recall metrics.

Fig.7. shows the real-world coordinates in the training dataset of three multi-floor buildings and the coordinates estimated by the proposed method. When Fig.7 is examined,

TABLE 3. UJIIndoorLoc dataset comparison of deep learning-based models.

Ref.	Building and Floor Accuracy	Building Accuracy	Floor Accuracy	MSE
Jang et al. [4]	95.41%	-	-	-
Alitaleshi *et al.* [5]	-	-	96.31%	8.34 m
Song *et al.* [15]	-	100%	96.03%	11.78 m
Kim et al. [19]	-	99.82%	91.27%	9.29 m
Ayınla *et al.* [21]	-	-	-	8.28 m
Our Study	**-**	**-**	**95.58%**	**4.55 m**

TABLE 4. Tampere dataset comparison of deep learning-based models.

Ref.	MSE
Song *et al.* [15]	10.88 m
Ayınla *et al.* [21]	9.52 m
Our Study	**8.13 m**

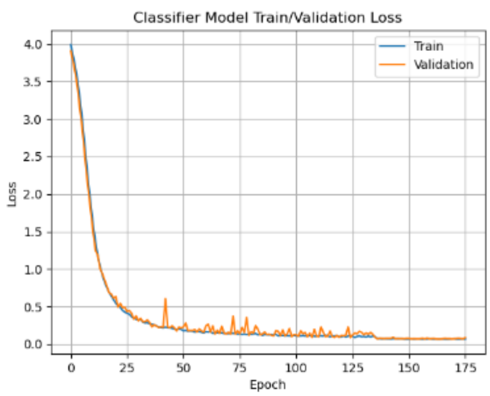


FIGURE 5. UJIIndoorLoc dataset classifier model loss during the training and validation phase.

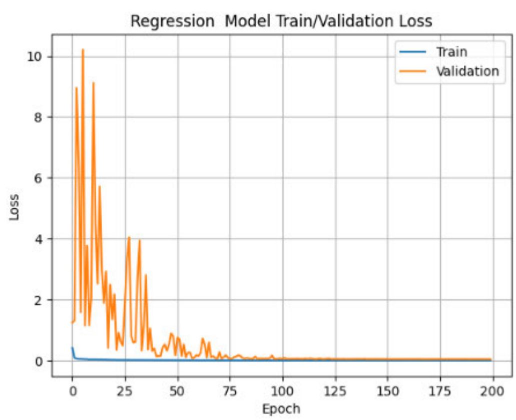


FIGURE 6. UJIIndoorLoc dataset regression model loss during the training phase.

it appears that there is a small margin of error between the estimated location and the actual location and they are in the same place.

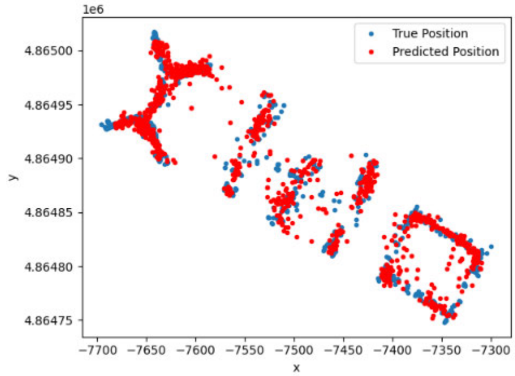


FIGURE 7. UJIIndoorLoc dataset predicted and ground truth.

The proposed model aims to combine two key elements, autoencoder and convolutional neural network (CNN), to obtain more meaningful features and achieve more effective results in indoor positioning. With this approach, more accurate classification and regression results were achieved.

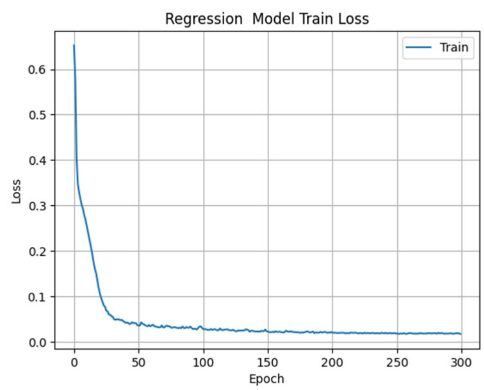


FIGURE 8. Tampere dataset regression model loss during the training phase.

FIGURE 9. Tampere dataset regression model test error.

Fig.8. presents the loss visualization encompassing the outcomes of the training phase conducted on the Tampere dataset. Fig.9. illustrates the graph depicting test error

progression. It was noted that the test error exhibited a decline until reaching 200 epochs, after which it stabilized, remaining constant thereafter.

All experiments were implemented in Python with the Pytorch library in Google Colaboratory, and the simulations were run on a machine with NVIDIA Tesla T4 on Colab Cloud.

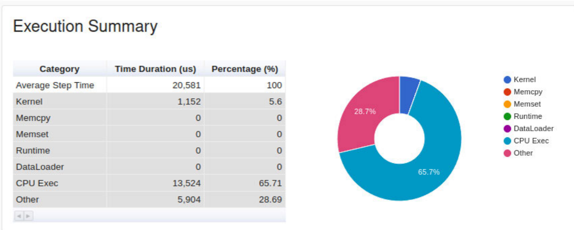


FIGURE 10. Proposed model execution summary.

B. PERFORMANCE ANALYSIS

One of the other contributions of our study is the runtime analysis to show the real-time operability of the proposed method. As a result, it has been shown that the method works on the GPU with a very small time cost. To use the runtime analysis of the designed model, the profiler API of the PyTorch library was used. This analysis is visually visualized in the TensorBoard setup. The analysis results of the proposed model are given in Fig.8. As seen in Fig.8, the average step time of our model was measured as 20,581 microseconds. Considering the testing period, the proposed model has a high potential to be used for real-time indoor localization. In some critical situations, people need to be located rapidly, especially in areas such as airports, healthcare facilities, companies and workplaces, conference centers, and educational institutions. We believe that the short running time of our model will be useful in real-time applications requiring emergencies.

V. CONCLUSION

In this study, a solution to the indoor localization problem with Wi-fi fingerprint in a multi-building and multi-floor system is proposed. The proposed solution is based on an autoencoder coupled convolutional neural network model. Due to the structure of Wi-Fi fingerprint data, using it directly results in an ineffective solution. For this reason, more meaningful features were extracted by using Wi-Fi fingerprint with autoencoder. This data was used as input to the convolutional neural network. Thus, a compact and high floor hit rate accuracy for classification and low localization errors were achieved.

As can be seen from the literature, the problem has been modeled with many different approaches such as CNN and LSTM. In wireless network experiments, it has been observed that convolutional neural networks successfully learn the relationship between access points. Therefore, this study aims to achieve the highest possible floor hit rate accuracy with a low-complexity network.

In many studies using autoencoders, it has been observed that the autoencoder network is also trained and combined with other networks recommended in those studies. Contrary to these studies, an autoencoder architecture that is trained simultaneously with a convolutional neural network is proposed in our model. A combined loss was used for the model created by combining the autoencoder and the convolutional neural network. By combining the loss function defined in the autoencoder with the loss function defined in the CNN, the networks were trained simultaneously, and high success was achieved as a result of the tests.

Since the UJIIndoorLoc dataset is the largest and open-access indoor dataset in the literature, we used this dataset in our study. Our method successfully classified the floor information label retrieved from the open-access UJIIndoorLoc database. There are two splits in this data set: train and validation. In certain studies, researched in the literature, it has been observed that results were obtained by combining the train and validation data of the UJI data set. In this study, the original validation data in the data set was used as test data. This is the case in all other important studies.

When the experimental results were examined, it was seen that the proposed model was successful with a floor hit rate of 95.58% and x, y localization error of 4.55 m. In some studies examined, the mean error in x, y localization for the UJIIndoorLoc data set was generally calculated for a single building. The mean error in the x, y localization obtained as a result of the testing of our model was calculated for three buildings in the UJIIndoorLoc data set. Compared to the current method examined, our model showed a 45.44% reduction in x, y localization error compared to the study with the lowest x, y localization error.

Our methodology proficiently computed the x and y coordinates for localization, leveraging the openly accessible Tampere database, achieving optimal performance at the minimum error threshold. The average error in x, y localization obtained as a result of the tests of our model was calculated for the Tampere data set. The proposed model was successful with an x, y localization error of 8.13 meters.

Our proposed method not only improves performance with fewer parameters but also adds speed and real-time operability. The method modeled only with CNN has achieved very high floor hit rate accuracy without other current approaches. The use of sequential models in solving indoor localization problems is open to debate. The complexity of these models is greater than convolutional networks.

Two separate study topics were determined for this study as future works. First, the autoencoder structure was used to map the input data to a more meaningful space instead of dimension reduction. For this reason, in future studies, instead of an autoencoder, research can be done on an approach that both makes the data more meaningful and reduces its size. Secondly, in training, the error function that trains the autoencoder and the convolutional neural network together was adjusted ad-hoc to give the highest accuracy. Instead, an adaptive error function needs to be investigated.

REFERENCES

[1] M. Youssef and A. Agrawala, "The Horus WLAN location determination system," in *Proc. 3rd Int. Conf. Mob. Syst. Appl. Serv. MobiSys*, 2005, pp. 205–218, doi: 10.1145/1067170.1067193.

[2] J. Torres-Sospedra, R. Montoliu, A. Martínez-Usó, J. P. Avariento, T. J. Arnau, M. Benedito-Bordonau, and J. Huerta, "UJIIndoorLoc: A new multi-building and multi-floor database for WLAN fingerprint-based indoor localization problems," in *Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN)*, Oct. 2014, pp. 261–270, doi: 10.1109/IPIN.2014.7275492.

[3] E. S. Lohan, J. Torres-Sospedra, H. Leppäkoski, P. Richter, Z. Peng, and J. Huerta, "Wi-Fi crowdsourced fingerprinting dataset for indoor positioning," *Data*, vol. 2, no. 4, pp. 1–16, 2017, doi: 10.3390/data2040032.

[4] J. W. Jang and S. N. Hong, "Indoor localization with WiFi fingerprinting using convolutional neural network," in *Proc. Int. Conf. Ubiquitous Futur. Netw. (ICUFN)*, Jul. 2018, pp. 753–758, doi: 10.1109/ICUFN.2018.8436598.

[5] A. Alitaleshi, H. Jazayeriy, and J. Kazemitabar, "EA-CNN: A smart indoor 3D positioning scheme based on Wi-Fi fingerprinting and deep learning," *Eng. Appl. Artif. Intell.*, vol. 117, Jul. 2022, Art. no. 105509, doi: 10.1016/j.engappai.2022.105509.

[6] A. E. Ahmed Elesawi and K. S. Kim, "Hierarchical multi-building and multi-floor indoor localization based on recurrent neural networks," in *Proc. 9th Int. Symp. Comput. Netw. Workshops (CANDARW)*, Nov. 2021, pp. 193–196, doi: 10.1109/CANDARW53999.2021.00038.

[7] M. Nowicki and J. Wietrzykowski, "Low-effort place recognition with WiFi fingerprints using deep learning," in *Advances in Intelligent Systems and Computing*, vol. 550, 2017, pp. 575–584.

[8] R. S. Sinha and S. H. Hwang, "Comparison of CNN applications for RSSI-based fingerprint indoor localization," *Electronics*, vol. 8, no. 9, p. 989, 2019, doi: 10.3390/electronics8090989.

[9] G.-S. Wu and P.-H. Tseng, "A deep neural network-based indoor positioning method using channel state information," in *Proc. Int. Conf. Comput., Netw. Commun. (ICNC)*, Mar. 2018, pp. 290–294, doi: 10.1109/ICCNC.2018.8390298.

[10] M. Abbas, M. Elhamshary, H. Rizk, M. Torki, and M. Youssef, "WiDeep: WiFi-based accurate and robust indoor localization system using deep learning," in *Proc. IEEE Int. Conf. Pervasive Comput. Commun. (PerCom*, Mar. 2019, pp. 1–10.

[11] H. Y. H. Zhu and L. Cheng, "Neural-network-based localization method for Wi-Fi," Tech. Rep., 2023.

[12] J. Kim, M. Ji, J. Il Jeon, S. Park, and Y. Cho, "K-NN based positioning performance estimation for fingerprinting localization," in *Proc. Int. Conf. Ubiquitous Futur. Netw. (ICUFN)*, Aug. 2016, pp. 468–470, doi: 10.1109/ICUFN.2016.7537073.

[13] L. Calderoni, M. Ferrara, A. Franco, and D. Maio, "Expert systems with applications indoor localization in a hospital environment using random forest classifiers," *Exp. Syst. Appl.*, vol. 42, no. 1, pp. 125–134, 2015, doi: 10.1016/j.eswa.2014.07.042.

[14] F. Yu, M. H. Jiang, J. Liang, and X. Qin, "An indoor localization of WiFi based on support vector machines," *Adv. Mater. Res.*, vol. 930, pp. 2438–2441, May 2014, doi: 10.4028/www.scientific.net/AMR.926-930.2438.

[15] X. Song, X. Fan, C. Xiang, Q. Ye, L. Liu, Z. Wang, X. He, N. Yang, and G. Fang, "A novel convolutional neural network based indoor localization framework with WiFi fingerprinting," *IEEE Access*, vol. 7, pp. 110698–110709, 2019, doi: 10.1109/ACCESS.2019.2933921.

[16] Y. Zhao, W. Gong, L. Li, B. Zhang, and C. Li, "An efficient and robust fingerprint-based localization method for multifloor indoor environment," *IEEE Internet Things J.*, vol. 11, no. 3, pp. 3927–3941, Feb. 2023, doi: 10.1109/JIOT.2023.3298603.

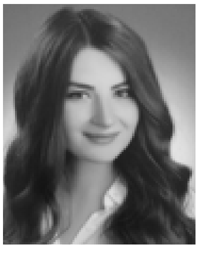
[17] W. Shao, H. Luo, F. Zhao, H. Tian, J. Huang, and A. Crivello, "Floor identification in large-scale environments with Wi-Fi autonomous block models," *IEEE Trans. Ind. Informat.*, vol. 18, no. 2, pp. 847–858, Feb. 2022, doi: 10.1109/TII.2021.3074153.

[18] B. Jia, W. Qiao, Z. Zong, S. Liu, M. Hijji, J. D. Ser, and K. Muhammad, "A fingerprint-based localization algorithm based on LSTM and data expansion method for sparse samples," *Futur. Gener. Comput. Syst.*, vol. 137, pp. 380–393, 2022, doi: 10.1016/j.future.2022.07.021.

[19] K. S. Kim, S. Lee, and K. Huang, "A scalable deep neural network architecture for multi-building and multi-floor indoor localization based on Wi-Fi fingerprinting," *Big Data Anal.*, vol. 3, no. 1, 2018, doi: 10.1186/s41044-018-0031-2.

[20] V. Bellavista-Parent, J. Torres-Sospedra, and A. Pérez-Navarro, "Comprehensive analysis of applied machine learning in indoor positioning based on Wi-Fi: An extended systematic review," *Sensors*, vol. 22, no. 12, 2022, doi: 10.3390/s22124622.

[21] S. L. Ayinla, A. A. Aziz, and M. Drieberg, "SALLoc: An accurate target localization in WiFi-enabled indoor environments via sae-ALSTM," *IEEE Access*, vol. 12, pp. 19694–19710, 2024, doi: 10.1109/ACCESS.2024.3360228.



HATICE ARSLANTAS received the B.Sc. and M.Sc. degrees in computer engineering from Erciyes University, where she is currently pursuing the Ph.D. degree. She is a Research Assistant with the Department of Computer Engineering, Erzincan Binali Yildirim University. Her research interests include wireless communication, indoor localization, and deep learning for localization.

SELCUK OKDEM received the B.Sc., M.Sc., and Ph.D. degrees in computer engineering from Erciyes University, Turkey. His Ph.D. thesis was focused on the wireless sensor network routing protocols. He is currently an Associate Professor with the Department of Computer Engineering, Faculty of Engineering, Erciyes University. His research interests include wireless networks, the Internet of Things, metaheuristics algorithms, and embedded systems.