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Research Article

Mobile Application Based Indoor Routing System Using Transfer Learning

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ABSTRACT

Nowadays, indoor routing in places with complex multi-storey architecture such as hospitals, shopping malls, parking garages and public buildings is traditionally carried out using signage or devices in a fixed position. When we examine the literature, it is generally seen that indoor orientation studies for certain needs are seen. The fact that the routing systems are fixed, and the signage is not an effective tool constitutes the motivation of this study. In this study, an image-based mobile application that is hardware-independent and adaptable to other interior spaces has been implemented using a mobile device. The application basically consists of two parts. In the first part, transfer learning based MobileNetV2 architecture is used to determine the initial store location. The proposed model detects the store signage image taken from the camera with 96% success. In the second part, the user is successfully guided to the target using the Dijkstra algorithm. With the developed mobile application, the user can reach the targets on the same or different floors in the fastest way without wasting time and without asking anyone. The application was tried in real time in a shopping center and successful results are obtained.

Keywords: *Dijkstra algorithm, Indoor navigation, Transfer learning*

Transfer Öğrenme Kullanılarak Mobil Uygulama Tabanlı İç Mekan Yönlendirme Sistemi

ÖZ

Günümüzde hastaneler, alışveriş merkezleri, kapalı otoparklar ve kamu binaları gibi karmaşık çok katlı mimariye sahip yerlerde iç mekan yönlendirmesi geleneksel olarak tabelalar veya sabit konumdaki cihazlar kullanılarak gerçekleştirilmektedir. Literatürü incelediğimizde genel olarak belirli ihtiyaçlara yönelik iç mekan yönlendirme çalışmalarının yapıldığı görülmektedir. Yönlendirme sistemlerinin sabit olması ve tabelaların etkili bir araç olmaması bu çalışmanın motivasyonunu oluşturmaktadır. Bu çalışmada, mobil cihaz kullanılarak donanımdan bağımsız ve diğer iç mekanlara uyarlanabilen, görüntü tabanlı bir mobil uygulama gerçekleştirilmiştir. Uygulama temel olarak iki bölümden oluşmaktadır. İlk bölümde, ilk mağaza konumunu belirlemek için transfer öğrenme tabanlı MobileNetV2 mimarisi kullanıldı. Önerilen model, kameradan alınan mağaza tabela görüntüsünü %96 başarı ile tespit etmektedir. İkinci bölümde kullanıcı Dijkstra algoritması kullanılarak hedefe başarılı bir şekilde yönlendirilmektedir. Geliştirilen mobil uygulama ile kullanıcı aynı veya farklı katlardaki hedeflere zaman kaybetmeden ve kimseye sormadan en hızlı şekilde ulaşabilmektedir. Uygulama gerçek zamanlı olarak bir alışveriş merkezinde denenmiş ve başarılı sonuçlar alınmıştır.

Anahtar Kelimeler: *Dijkstra algoritması, İç mekan navigasyon, Transfer öğrenme*

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I. INTRODUCTION

Increasing the world population, large architectural structures such as hospitals, airports, shopping malls, garages and underground train stations are being built. These multi-storey buildings, which are built to meet the building need, cause the increase and complexity of urban structures. In addition, finding a way in the building and reaching the desired place in the fastest and shortest way cause a separate problem. Therefore, people prefer to use guidance systems to make their lives easier. Satellite-based Global Positioning System (GPS); It is widely used in many fields such as navigation, map making, geology, search and rescue and defense industry [1]. For example, on a large university campus, students' GPS information on their smartphones was used to determine the duration, frequency, and time students spend on campus [2]. However, GPS cannot be used successfully in closed areas due to structures such as roofs and walls that block the satellite signal [3]. Therefore, indoor navigation systems are needed.

Wireless technologies such as Wi-Fi, Zigbee, Bluetooth, Ultra-Wideband (UWB), Radio-Frequency Identification (RFID) are used for object location detection in indoor areas, independent of satellite-based systems [4]. These technologies affect life positively for orientation in buildings such as hospitals, public buildings, shopping malls. Murata et al. developed a probabilistic localization algorithm that utilizes mobile device inertial sensors and Received Signal Strength (RSS) from Bluetooth Low Energy (BLE) beacons for visually impaired people. Field experiments were realized with impaired people confirm the practical performance of the proposed system in very big shopping mall [5]. In another study, they developed a smart phone application with a QR tags that are a clue for individuals with cognitive disabilities. Generally, individuals with cognitive disabilities can find direction at work, school or hospital with a caregiver or guide until they get used to the place. QR codes placed on a certain route will be useful for the person to go to their location and destination easily, cheaply and on their own. Authors stated that their field experiments with 14 cognitively impaired users yielded successful results. Thus, these people will be able to navigate individually in unfamiliar indoor spaces [6]. In daily life, people spend more time indoors than outdoors. Despite this, the success of indoor positioning systems still does not provide usability and accuracy comparable to GPS [7, 8]. Because tracking the location of the object or person indoors is an important factor. For this reason, various studies are carried out using many techniques such as Wi-Fi, Bluetooth, Zigbee, UWB, RFID technologies, as well as machine learning and deep learning, for successful indoor routing [9, 13].

Navigation systems are one of the important systems that make human life easier. The development of communication technologies and smart devices has supported the use of navigation systems. People prefer to use these systems in different areas. After outdoor navigation, people also prefer these systems in large buildings such as hospitals, airports, train stations [14].

Indoor navigation systems can be elaborated as Computer Vision, Communication Technology and Pedestrian Dead Reckoning. Computer vision-based systems use omnidirectional cameras, 3D cameras, or smartphone cameras to obtain information about indoor environments. These images are made sense for routing and location knowledge by methods such as Speeded Up Robust Feature, Scale Invariant Feature Transform, machine learning, and deep learning [15]. Zhang et al. performed indoor scene and object recognition inside the MIT building using a Deep Convolutional Neural Network (DCNN). They used DCNN to perform position recognition based on spatial features. They created more than 600,000 2D and 3D images of the endless corridors of MIT buildings with camera and phone. The accuracy of the proposed model is 81.72% and 94.39%, respectively. Thus, it has been determined that DCNN successfully makes sense of places like people. The authors stated that indoor orientation will be made in their future studies [16].

Recently, autonomous robot navigations have been widely used. However, challenges such as environmental factors, light conditions, sensor limitations, and messy indoor environments negatively affect robot navigation. DCNN is used in situations such as determining the door location in indoor navigation where the image quality is affected. Model trainings are made according to different poses of the door. After the door location is determined, the movement of the robot when it approaches the door can be determined and indoor navigation can be created successfully [17].

In another study, the interior spaces such as kitchen, bathroom, bedroom, living room, which are most used in daily life were determined for blind and visually impaired persons. Using the EfficientNet architecture, 95.60% success accuracy was achieved with the MIT 67 dataset [18].

Developments in vehicle technology contribute to the production of vehicles with more features. However, GPS does not work indoors such as in a parking. Kumar et al. propose an indoor positioning system for vehicles called eValet. They have placed cameras in certain parts of the closed parking. Convolutional Neural Networks (CNN) detects whether the moving image on the camera is a vehicle or not. Using the Homography Transformation, the closest point of the vehicle to the ground is converted into geographic coordinates. Thus, latitude and longitude values are determined for each object determined as a vehicle on the image. In this study, they obtained more successful results than their previous application with Haar-like feature classifier algorithm for indoors using CNN [19].

Deep learning architecture is used successfully in the detection of living things as well as in inanimate object detection. Home accidents play an important role in the lives of elderly and lonely people. For this reason, Sultana et al. propose a human fall detection system. They detect human falls using CNN and Recurrent Neural Network architectures in the images obtained from the camera placed in the room. They achieved a 98% success rate in images obtained from different cameras. In their next work, they will improve the system by adding a warning system [20].

Low-cost Nano Aerial Vehicles (NAVs) offer a new autonomous inspection framework in indoor evaluation studies. In another study using nano aerial vehicles, obstacles were detected with a human perspective brought to aircraft. Obstacle avoidance steps were carried out by checking the potential existence of any obstacle with the navigation algorithm. The application, which geotags the image when no obstacle is detected, offers autonomous navigation and obstacle avoidance with guidance [21].

In another indoor navigation study, where pedestrians were guided indoors and users were able to track indoor and outdoor locations, the guidance solution in large areas was provided efficiently. In the study, where a deep learning approach was used for automatic classification of landmarks, model relationships for both performance and salience of landmarks were determined with the data obtained from the images, and an indoor navigation system for pedestrians was presented as an android application [22].

Different categories such as obtaining location information, interpreting the information, and determining routing steps are also preferred in machine learning and deep learning architectures routing studies [23].

As seen in the literature, deep learning architecture, which is used in different areas, shows good success in making sense of the image in the interior. For this reason, MobilNet architecture is used in this image-based study. MobilNet architectures are a deep learning architecture designed to perform more efficient work on mobile devices and embedded systems [24].

In addition, in the literature, it is seen that smart devices and cameras are preferred because of their ease of use in many studies on routing [25-27]. It is generally used for data collection, audio, and video guidance.

In navigation systems, guiding the person to the target with the best route is as important as determining the location of the person. In many indoor navigation studies, the shortest route is preferred firstly. In addition, it is aimed to optimize the cost of location detection, power, and memory consumption. Looking at the literature, First Fit, Best Fit, Dijkstra, Location Aware and Remembering

Navigation (LARN), HCTNav, modified A*, depth-first, Flexible Path Planning, trilateration, D*, k-NN, PF, PDR, and triangulation algorithms are mostly preferred [28]. Dijkstra Algorithm (DA) and A* are among the popular algorithms [29]. DA is a mature shortest pathfinding algorithm between the start position to destination based on reference nodes. It takes a short time and is not very complex with high performance for not very large data. Therefore, it is preferred in many studies.

Xu et al. They propose a personalized pedestrian guidance application to reduce obstacles on the route in a closed shopping center. The best path between the starting and target shop for user is created with DA. The priority of the features taken into consideration while creating the route is determined as the store to be visited, the distance and the roughness on the road. For example, if the user on the second floor will go to the store on the first floor, he or she is guided by the elevator despite the information that he will not prefer the elevator. Because the priority in the study is to reach the target store. The same floor orientation situations, the platform on which the system was developed, and user experiences were not presented in the study [29].

Gao et al. propose a smart phone-based parking guidance system in their study. The system offers the most suitable parking place and driving route recommendation according to the driving distance, in-car travel time, walking time, parking fee, parking space search time and parking space type. The user sends a request to the system using the application for a parking request. The system determines the most suitable route according to the criteria using DA and sends it to the user's phone. In the system based on C/S architecture, the server side is Windows Server 2000 and the MySQL database is developed using the client side Android platform. Baidu Map was preferred for the visualization of the route [30]. Here, the smartphone is used only for sending and displaying requests. Another smartphone-based parking guidance system has been developed using a QR code. The QR code, which is decoded using a smartphone, contains the identification number of the vehicle. In the SQLite database, there is location information that matches the vehicle's identification number. According to this location information, the optimum route to go to the vehicle is determined by DA. User directions are created according to pedometer rules. The authors tried the application in a large parking lot and stated that they provided a successful orientation [31].

Uddin and Suny propose an application to facilitate the life of the visually impaired. The system includes two main modules: direction with voice commands with smart phone and detecting any obstacle on the road with ultrasonic sensor. After the visually impaired person gives the target location as a voice command, the system determines the shortest path between the source and the target using DA. When an obstacle is detected on the road with the ultrasonic sensor, the distance of the obstacle is calculated by the microcontroller. The necessary data is sent to the smart phone using the Bluetooth module and is given to the visually impaired person as a voice instruction. The system has limitations such as lack of GPS data and not updating Microsoft Bing Map [32].

As seen in the literature, technologies such as QR code, Beacon, Bluetooth and RFID and DA are preferred in mobile application-based studies [33-35]. Because the complexity of DA is acceptable for pedestrian navigation.

DA is a greedy algorithm used to determine the shortest path and solves the optimization problem. The basic logic of DA is to add the shortest point relative to the starting point and update the shortest distance and it is suitable for use in this study given a single source and all nodes. When a decision needs to be made, he chooses the best option available at the time. Based on Broad Scope Search (BSF), this algorithm searches the path from the starting point to all points; it is a method of exploring broadly before exploring in depth. DA is use because it is difficult to express the shortest distance when store distances between floors are taken into account. DA is preferred in this study because pedestrian guidance is made according to the optimum route between the starting and target location in a building with the same or different floor layout. An algorithm using a heuristic approach is not preferred because instant location information is not used.

Most of these problems constitute the motivation of the study. The aim of the routing studies is to guide the user from one point to another target point with route information. In this study, it is aimed for the person to go to his destination by using own phone indoors, using the low cost, easy, accurate, real-time, and shortest route. Thus, it is expected to reach its destination easily indoors without the need for additional hardware, guides, and sign. The main contributions and steps can be listed as follows:

- The developed mobile-based application includes the floor plans of a shopping mall. Thus, it can be updated for every shopping mall with a floor plan.
- With the mobile application, the user takes the picture of the store in his/her location with the phone camera. No additional hardware or internet connection is required and is low cost. In addition, the user easily selects the name of the store he will visit from the menu in the application according to the floor plan. Since it is a picture-based orientation application, it can be adapted in large spaces such as hospitals and factories.
- The name of the store is determined using the Transfer Learning architecture from the image of the starting point where the user is located, and the coordinates of the store are determined by matching with the floor plan information. Therefore, no signal information is required for position information.
- The shortest route between the starting and target store is determined in real time by DA. The mobile application visually presents the route on the floor plan.
- The designed deep learning-based mobile application has been tested with users' phones in a shoppng mall in Istanbul, Turkey, and its accuracy has been determined to work in multi-story buildings.

Other parts of the study are as follows: Material and Methods are mentioned in Section 2. Experimental results and analysis are presented in Section 3. Conclusion and future works are told in last Section 4.

II. MATERIAL AND METHOD

A. DATASET

Floor plans and store information of many shopping centers in Turkey are published on their own web pages. In this study, Buyaka shopping center in Istanbul is preferred [36]. There are 158 different stores in the six-floor Buyaka shopping center. Since there are not enough images of the stores on the website, images of different angles and sizes are collected from inside the shopping mall. Since the obtained images would not be sufficient for the performance of the model, data augmentation is performed. There are many preprocessing techniques such as cleaning, reducing, transforming, merging on the data [37]. With these techniques, the meaning of the data, the detection of missing data, resizing, normalization is provided, and it is made suitable for the purpose of use. For this reason, 8536 images are obtained by affine transformation (translation, rotation, scaling). Store names in the images have been blurred to avoid using trademark names in the article. Sample images of the prepared dataset are shown in Figure 1.

Figure 1. *Sample images of some stores.*

8536 input image datasets with 3-channel color information are converted to level images and the data size is determined as 224 x 224. To convert the gray level pixel values in the range of 0-255 to the range of 0-1, the Max-Min Normalization process seen in equation (1) is performed. Thus, 0: Black, 1: White, and the gray level values in between are represented by their closeness to 0 and 1. In Equation (1), x: gray level pixel value; (x): smallest gray level pixel value; (x) : largest gray level pixel value; x': stands for normalized data.

$$x' = (x - (x)) \div (max(x) - min(x)) \quad (1)$$

A. 1. Classification of Store Images With MobileNetV2

Deep learning has been used successfully in many classification problems [38-40]. CNN is one of the most popular deep learning models. CNN is a multi-layered forward-looking artificial neural network with its ease of use, parallel operation, and high success capability. The success of CNN is demonstrated in many studies such as classification, object recognition and detection, natural language processing, and text analysis [41, 42]. There are different CNN architectures such as AlexNet, VGGNet, ResNet, MobileNet. These architectures differ in the number of layers and learnable parameters. MobilNet architectures are a deep learning architecture designed to perform more efficient work on mobile devices and embedded systems [24]. Thus, performance loss in mobile devices is prevented with light models [43]. Models with deeper convolutional architecture can be created with the MobileNet architecture [44]. MobileNet has different versions such as MobileNetV1, MobileNetV2, MobileNetV3 according to usage area and structural changes. Unlike MobilNetV1, MobileNetV2 has linear bottlenecks between the layers and shortcut connections between the bottlenecks [45]. Unlike MobilNetV2, MobilNetV3 has activation functions. In this study, MobilNetV2 is preferred because it is an architecture developed for the operation of image processing applications on mobile devices.

In our study, feature vectors of images trained with MobileNetV2 architecture on ImageNet dataset [46] are used for transfer learning model. First, the training image dimensions are arranged as (224,224,3). After performing the necessary normalization process, using the feature vectors of the MobileNetV2 model, the dropout layer is added and the model design suitable for the study is carried out with the change made in the classification layer. The learning rate, which indicates the update rate of the weights learned during the training of the model, was determined as 0.001. Categorical cross entropy function was used to calculate the loss between the model's prediction result and the real value. The Adam optimization algorithm was preferred because the learning rate can be updated for different parameters, is computationally efficient, and requires low memory requirements. The general flow of the model designed in the study is shown in Figure 2 and the model architecture created in Table 1.

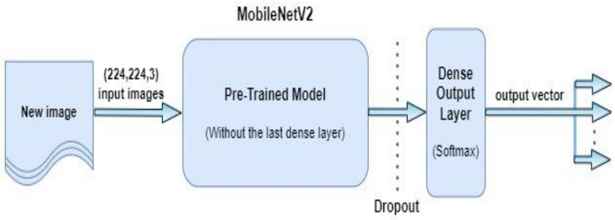


Figure 2. *Overview of the designed model.*

Table 1. *The general MobileNetV2 architecture.*

Layer (Type)	Output Shape	Parameters
keras-layer (KerasLayer)	(None, 1280)	2257984
dropout (Dropout)	(None, 1280)	0
dense (Dense)	(None, 158)	202398

MobileNetV2 uses a linear bottleneck structure to reduce the input size. The Bottleneck layer is used to extract features from the high dimensional space without much loss of information. This layer combines the linear activation function and the 1x1 convolution filter. These shortcut connections that make up the residual connection structure greatly reduce memory costs. The bottleneck layer structure of model is shown in Figure 3.

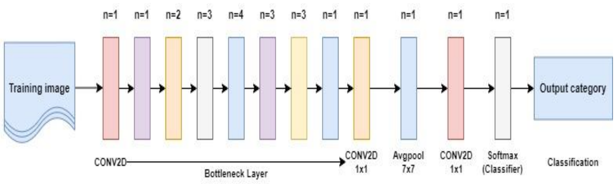


Figure 3. *Overview of the designed model.*

A.1.1. Adapting MobileNetV2 Model to Tensorflow Lite

TensorFlow-Lite is a toolkit that enables more efficient use of Tensorflow models on embedded systems and mobile devices. It enables the learned models to be used on mobile devices with less latency. It also offers APIs for many programming languages by supporting different platforms such as Android and IOS. The proposed model for the classification of store images is saved as a .tflite file to be used in the Android environment together with the conversion process and is used in the Android environment with the label file containing the store names.

A.1.2. Routing Using The Dijkstra Algorithm

A graph is a non-linear data structure consisting of vertices and edges. Graphs are represented as N(Node)= {N0, N1, N2…}; E(Edge)= {E0, E1, E2…}; G(Graph)= {N, E}. N, E, G respectively represent Node, Edge, Graph. Graph model can be used for any application that has a connection between them based on distance/relations. In this study, the floor plans of the shopping center are considered as a graph model. The door numbers of the stores represent the corners/nodes. The roads connecting the stores represent the edges.

In the study, the route information between the start and destination point is obtained with the DA. The route information is presented to the user on the floor plans of the relevant floors. Relationships between neighboring stores are discussed in the routing operations on the same and different floors. In the routing processes between different floors, routing is carried out by considering the elevator information at the nearest point. The sample floor plan image used in the study is shown in Figure 4.

Figure 4. *Buyaka shopping center floor plan [47].*

Considering the change of store names for each floor plan in the shopping center, an adjacency matrix indicating the neighborhoods between the door numbers is created. The general equation of the adjacency matrix is seen in Equation (2).

$$\begin{cases} if\ (Ni, Nj) or (Nj, Ni) \in E & ,1 \\ \quad\quad otherwise & ,0 \end{cases} \tag{2}$$

Here, Ni and Nj represent two nodes, E represents edges. When constructing the adjacency matrix for a simple graph model, if the Ni and Nj points have a neighborhood with each other, the neighborhood can be specified both from Ni node to Nj and from Nj node to Ni. In the adjacency matrix created in this way, those who observe neighborhood statuses are represented by 1 and those who do not are represented by 0. The process of taking the neighborhood between the neighbors of the door number determined on the adjacency matrix, updating the nearest door information, and keeping the shortest path information are summarized as following algorithm:

1. Updating the shortest door distance information of all door numbers.
2. Determine the index of the selected door number (doorNumberIndex).
3. If the door is a door that has not been visited before (addedDoorNumber) and the distance information of the door (shortestDistances) is less than the shortest door distance (shortestDoorDistances) Determine the selected house number as the nearest door.
4. And update the shortest door distance (shortestDoorDistance).
5. Updating the transportation cost and the shortest distance information of the door numbers on the distance matrix.
6. Determine the distance information of the nearest door and the selected door number on the distance matrix.
7. If the distance information is greater than zero and the sum of the shortest door distance and the arrival cost is less than the short distance information of the door number.

8. Set the selected door number as the starting point for the next step and update the shortest distance information.

Building structures are stored in Javascript Object Notation (json) format to present the work to the user in the Android environment. For each floor plan, a json file containing information such as store name, door number, floor information and x, y point values of the floor plans placed on the canvas is created. A json file block in the form of “id: 27, doorNumber: 27, name: Arçelik, x: 637, y: 367, floor: B2” is created for each store in the floor plan.

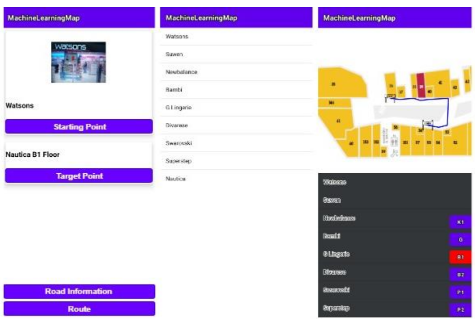
The store name information obtained with the classification model and the selected target store name information are associated with the door numbers in the relevant json files. The DA provides the route information between the selected door numbers over the neighborhood matrix. A class named Canvas is used for Android drawing operations. The route between the starting point and the destination point is made using a class called Canvas for Android.

III. RESULTS

In this study, a real-time application has been developed to guide the user in the building without monitoring the status of the person. The study is carried out on two foundations. First, a deep learning architecture is created to analyze the store images to determine the current location with the Android application. The second is the display of the route created with the shortest path algorithm on the mobile application, using the floor information of the building structures. In the study, MobilNetV2 architecture, which can achieve results quickly and successfully, was preferred as the deep learning architecture. This architecture was used because it was developed for mobile and embedded devices and required low computing power. The proposed model in the study is trained through Google Colab using Python language. The computer and library information for which the model is designed are as follows: Intel Core i5-7200U CPU @ 2.40 Ghz, Intel(R) HD Graphics 620, 8GB, Windows 10 Pro 64 bit, TensorFlow 2.5.0.

A. SAME AND DIFFERENT FLOOR ROUTING SCENARIO

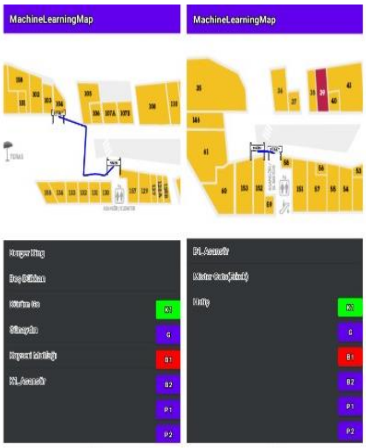
The application is first tested with the Android studio emulator Nexus 5X API 29. After determining the starting place where the user is located, the target store is selected. By checking the json file containing the floor information, the route information of the shortest route is created with DA according to the door numbers for the stores on the same floor. The names of the stores you will see while passing through this route are listed on the screen. Figure 5 shows the opening screen of the application and the route information for Watsons, the starting store, and Nautica, the target store, located on the same floor.



(a) (b) (c)

Figure 5.(a) *Selecting start and target name of the stores on the same floor using opening screen* ***(b)*** *Stores that the user will see on the route* ***(c)*** *Display of the created route on the floor plan.*

For stores located on different floors, guidance is made using the elevator information on the floor plans. The DA first creates the shortest elevator route. When the user comes to the same floor as the target store, the direction of the target store is realized with the shortest route according to the elevator. For example, Burger King and Hotiç are on different floors. The route information from upper floor to lower floor is shown on the screen in Figure 6. The operations are carried out in the same way from the ground floor to the upper floor.

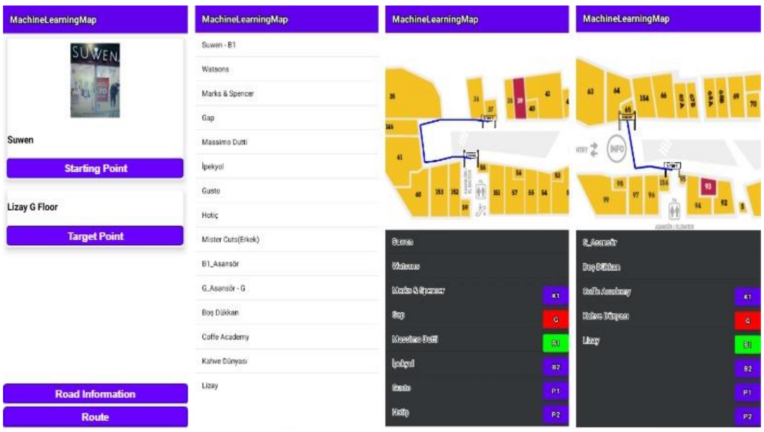


(a) *(b)*

Figure 6. ***(a)*** *Directing the user on the upper floor (K1) to the elevator* ***(b)*** *Directing the user going downstairs (B1) to the store.*

B. REAL-TIME TESTING OF THE APPLICATION

The application is tested in real time at the Buyaka shopping center using a Redmi 8A MIUI Global 12.0.3 smartphone. Routing guides in the application are shown in Figure 7. Routing videos on the same and different floors can be seen in the given links [48, 49].



(a) *(b)* *(c)* *(d)*

Figure 7. *In the routing process performed on a different floor* ***(a)*** *Determination start and target store name for initial information* ***(b)*** *Store names route information between target stores* ***(c)*** *routing information for different floor* ***(d)*** *route information shown on the floor plan where the target store is located.*

C. EVALUATION OF THE MODEL

Buyaka dataset is determined as 80% training and 20% as validation dataset. The designed model is trained with 6890 training images and 1646 validation images. Figure 8 and Figure 9 show the graphs of the model's accuracy and loss values for 200 epochs.

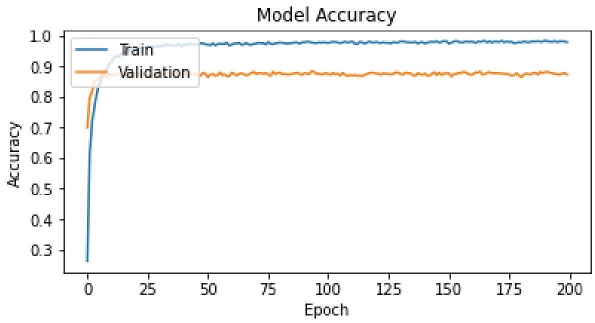


Figure 8. *Model accuracy for training and validation.*

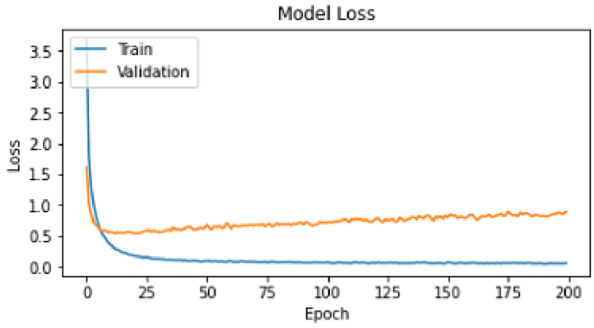


Figure 9. *Model loss graphic for training and validation.*

The model is run 200 epochs with a total of 8536 images and achieved 98% accuracy in the training process. For the test processes of the model, a total of 588 test image data belonging to 158 classes are prepared with data augmentation and 96% success is achieved. The accuracy value (Acc) is calculated with the formula in equation (3). In the equation, "True Positive (TP)" is the number of perfectly identified store pictures; The "True Negative (TN)" is the number of perfectly detected wrong; "False Positive (FP)" is the number of wrongly detected images as positive which is actually non correct, and "False Negative (FN)" is the number of correctly detected images as negative which is actually non correct. These values are found in the complexity matrix in Table 3. The correctly classified some sample test picture images are shown in Figure 10.

Figure 10. *Sample images of some stores.*

The performance of proposed approach for some classes is measured using Recall (R), Precision (P) and F1-Score metrics in Equation (4, 5, 6) in Table 3.

$$P(n) = \frac{TP}{TP + FP} \tag{4}$$

$$R(n) = \frac{TP}{\mathrm{TP} + \mathrm{FN}} \tag{5}$$

$$F1Score(n) = \frac{TP + TF}{\mathrm{TP} + \mathrm{TF} + \mathrm{FP} + \mathrm{FN}} \tag{6}$$

Table 3. *Performance values of some classes.*

Prediction Values	Newbalance	Oysho	Rossmann	Suwen	Swarovski	R	P	F1 Score
Newbalance	55	0	0	0	0	0.95	0.98	0.96
Oysho	0	48	0	0	0	0.93	0.97	0.95
Rossmann	0	0	44	0	0	0.94	0.97	0.95
Suwen	0	0	0	30	0	0.93	0.96	0.94
Swarovski	0	0	0	2	51	0.94	0.95	0.94

K-fold cross validation allows us to see if the high performance of the model is random. This method shows both whether we are facing an overfitting problem and the quality of the model. A 10-fold cross validation method is used to increase the validity of the created model. The success value and the average cross validation success value obtained in each fold of the model are shown in Table 4. The mean cross validation Acc value is calculated as 94%.

Table 4. *10- fold accuracy values of model.*

Fold1	Fold2	Fold3	Fold4	Fold5	Fold6	Fold7	Fold8	Fold 9	Fold 10	Average
92.61	92.84	96.43	94.63	93.42	93.15	94.84	94.63	93.41	92.10	94

The results of different navigation applications according to the hardware and software used in the interior are shown in Table 5. Although there are studies based on deep learning architecture in interior spaces, in this study a mobile guidance application specific to a single shopping center was implemented.

Table 5. *Different indoor navigation study results.*

Studies	Task	Score
Path planning for indoor mobile robot based on deep learning[50]	Indoor path planning	95.6%
Scene perception based visual navigation of mobile robot in indoor environment [51]	Indoor navigation	94.2%
Hybrid deep learning model based indoor positioning using Wi-Fi RSSI heat maps for autonomous applications [52]	Indoor navigation	88%
Multi goals and multi scenes visual maples navigation in indoor using meta-learning and scene priors [53]	Indoor navigation	80%
This study	**Indoor navigation**	**96%**

The results comparision of different classification and mobile application studies carried out with the MobileNetV2 architecture is shown in the Table 6. In our study, as a result of the training carried out with indoor images, a successful result was achieved in image classification and the user was guided through the classification model in the Android environment. The study also contributes to the use of the MobilNetV2 transfer learning approach in indoor spaces.

Table 6. *Different mobile application study results with MobileNetV2.*

Studies	Task	Score
Health protocol system: Face mask detection using deep transfer learning [54]	Feature extraction	99.24%
Android skin cancer detection and classification based on MobileNetV2 model [55]	Detection-classification	95%-70%
Classification of pollen-bearing honeybees using MobileNetV2 architecture [56]	Classification	91%
Diet application that can recognize Turkish foods with deep learning [57]	Detection	78%
This study	**Classification**	**96%**

IV. CONCLUSION

GPS information is not always sufficient for indoor navigation studies. For this reason, different hardware alternatives are offered to the user in indoor navigation studies. Hardware-based studies have cost and time constraints at the point of implementation. Therefore, in this application, the phone has been preferred in this application because it is a portable and widely used device.

In addition, the lack of GPS information at every point formed the main motivation of this study. This work can be used for any building with a floor plan. Transfer learning-based approach is used to determine the locations of the spaces, and 98% success is achieved in the training images and 96% in the test images. Since this is a real-time running app, the quality of the user's store images can affect the app's response time. Therefore, images should be clear and legible. For the application to work efficiently, the user must follow the given route. Since there is no instant location tracking in the study, the application must be restarted when a different route is entered. User feedback and store change status will be checked in the next versions of the application.

The application is image-based to be able to use it in places such as hospitals, factories, airports. For this reason, a direction is not made by typing the name of the starting and destination point as in normal navigation systems. It is planned to add a route tracking and voice warning system with a low-cost technology. The floor plan database of the application can be expanded by adding floor plans of different and popular shopping malls. Thus, the user who downloads the application can reach the store he is looking for in different shopping malls in a fast, easy, without asking anyone, and shortest way.

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