International Journal on Advanced Science Engineering Information Technology

Vol.14 (2024) No. 6
ISSN: 2088-5334

Children’s Accident Prevention System Based on Real-time Video Interpretation and GPS Information

HyunJoo-Park [a], Seungdo Jeong [a,*]

[a] *Department of Smart Information and Telecommunication Engineering, Sangmyung University, Cheonan, Republic of Korea*
*Corresponding author: *sdjeong@smu.ac.kr*

Abstract*—This paper proposes a smart badge system for children's safety. We implement semantic segmentation technology, GPS-based location tracking, and safety zone setting functions. First, we implemented a situational notification function using semantic segmentation technology. This system analyzes the child's surrounding environment in real-time to detect dangerous situations and provides immediate notification through a badge for children. This can raise children's traffic safety awareness and prevent jaywalking. Additionally, semantic segmentation technology, which can accurately recognize and classify objects in images, dramatically improves the accuracy of situational judgment. This can reduce unnecessary notifications and provide reliable notifications about actual risk situations. GPS-based real-time location tracking and safety zone setting functions were implemented. The child's real-time location can be checked on the guardian app through the GPS sensor built into the child's badge. This allows continuous monitoring of the child's safety status. Additionally, setting a child's safety zone in the guardian app immediately sends a notification to the guardian when the child leaves the safety zone, enabling crime prevention and rapid response. GPS-based technology improves the user experience by making it easier for guardians to determine their child's location. This system can be applied to various environments and situations and expanded to other child safety services. Additionally, the safety zone setting function helps relieve guardians' anxiety. This can be said to present an innovative solution to child safety.

***Keywords*—Classification; image segmentation; FCN; CNN; polyline; object detection; real-time video segmentation.**

Manuscript received 5 Aug. 2023; revised 21 Oct. 2023; accepted 16 Nov. 2024. Date of publication 31 Dec. 2024.

I. INTRODUCTION

Child traffic accidents and missing children are social problems that occur every year, resulting in injuries and even deaths of children. In 2020, the "aggravated punishment of child manslaughter in a child protection zone" was introduced to address these issues [1], [2]. However, despite these efforts, child traffic accidents have not decreased significantly. From March to September 2019, there were about 6,300 accidents, and from March to September 2020, when the "aggravated punishment for child fatalities in child protection zones" was implemented, there were about 4,830 accidents. However, this figure should also consider the impact of limited school attendance due to the coronavirus. According to the Traffic Accident Analysis System of the Korea Traffic Organization, jaywalking is the leading cause of traffic accidents among children, and it also occurs frequently at crosswalks. Due to the behavioral characteristics of children, even if a driver is traveling at a safe speed, an accident can occur due to a child jaywalking out of nowhere.

A steady stream of child-related accidents has made parents nervous about letting their children go out alone. Unaccompanied children are particularly vulnerable to being targeted by criminals, lack of safety awareness, and traffic accidents. While there are efforts to improve drivers' understanding of their duty to protect children, such as the "aggravated penalty for killing a child in a child protection zone," there has not been a significant effort to improve children's traffic safety awareness.

'Children's Smart Badge' is a work that proposes to solve these problems. It helps children improve traffic safety awareness and prevent traffic accidents by determining which direction the child faces on the road and directly notifying the child of the guardian's voice, which is stored differently depending on the situation [2]. In addition, the guardian can identify the child's real-time location and receive notifications such as leaving the safety zone to prevent crime or respond quickly in case of trouble. This helps keep children safe more effectively.

II. MATERIALS AND METHOD

We analyze the strengths and weaknesses of existing systems developed or researched to prevent road accidents and missing children [3], [4]. To date, three main types of technologies have been studied for traffic accidents and missing children. First, the 'smart crosswalk' provides contextual voice guidance by attaching motion sensors and speakers to the traffic light pole at a height of 2.5 meters. However, since the system provides voice prompts from the traffic light pole, children may have difficulty focusing on the voice prompts. It also has the limitation that it cannot be utilized in places without traffic lights. Second, the "Crosswalk LED Safety Guidance Block [5]" improves nighttime visibility by installing LED safety guidance blocks at crosswalk approaches. However, because this system uses LEDs, it focuses on visual effects and can be misinterpreted as a design element rather than a safety system. They also suffer from poor visibility during the day. Third, the "child location tracking system using GPS and Wi-Fi [6]" creates a safe zone by setting a secure location and a radius based on that location. However, the problem with this system is that it creates a safe zone in the form of a sphere with a radius of 100 meters, 300 meters, and 500 meters, which can cause blind spots. Therefore, there is a need to develop a new system that complements the shortcomings of these existing systems.

A. System Configure of Child Smart Badge

Fig. 1 shows the overall system configuration. The children's smart badge system consists of Jetson-nano, a badge for children to wear, an application for parents to use, and a server that communicates data from the two systems and analyzes GPS location information.

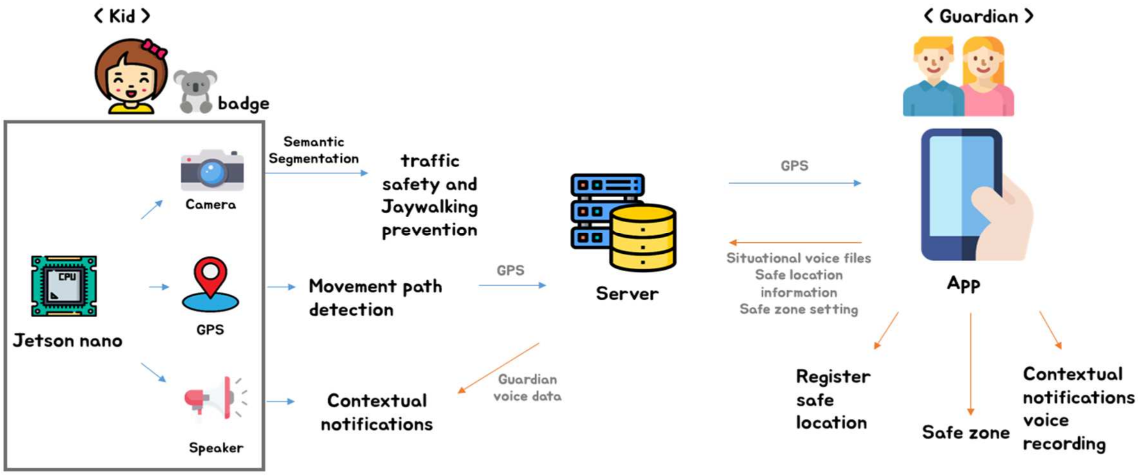

Fig. 1 System configuration diagram

First, the Jetson-nano has a camera, GPS module, speaker, and accelerometer. The camera captures the direction the child is looking at and performs semantic segmentation [7], [8]. The speaker determines the type of road [9], [10] and gives the parent voice notifications by situation to improve traffic safety awareness and prevent jaywalking [11]. The GPS module receives the child's GPS information and sends it to the server. Second, the application allows parents to set safe zones, record contextual parental voice notifications, and check the child's current location [12], [13], [14]. It also sends the contextual notification audio file and the set safe zone information to the server. Finally, the server performs the data communication function between Jetson-nano and the application. It analyzes the location information based on the GPS information [15], [16] received from Jetson-nano and sends the analyzed GPS information to the application. It also manages contextual notification voice files so that Jetson-nano can give contextual notifications through contextual notification voice files received from the application [17].

B. Keeping Children Safe on Foot

1) Configure the Child Smart Badge hardware: Jetson-nano is a small computer from NVIDIA that supports the development of deep learning applications with a quad-core ARM A57 as a CPU and a 128-core Maxwell as a GPU. Jetson-nano basically comes with only the main board, and peripherals are prepared separately as shown in Fig. 2.

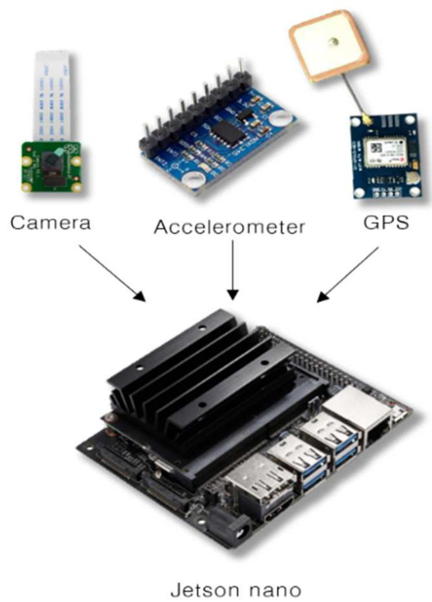

Fig. 2 Hardware Configuration

The camera module uses the IMX219-8MP model to enable image processing such as semantic segmentation on the terminal (Smart Badge). The GPS module uses the NEO-7M model to perform real-time device positioning with an error range of 5 to 10 meters. The acceleration sensor module uses the digital acceleration-ADXL345 model to detect jaywalking, considering that the Jetson-nano does not have an analog input pin.

2) Image Processing: To improve children's traffic safety awareness and prevent jaywalking, we used semantic segmentation technology and used FCN (Fully Convolutional Networks) model. Fully Convolutional Networks (FCN) [18] is a model that modifies the existing CNN [19],[20] model to be suitable for segmentation. CNNs [20] for image classification, such as AlexNet and VGGNet, consist of convolutional and fully connected layers. As the CNN enters the fully connected layers at the end of the network, spatial/location information is lost, and it is impossible to know where the objects in the image are located. Also, the size of the input image is fixed for the network. FCN [18], on the other hand, replaces the fully connected layer, which only accepts fixed-size inputs, with a 1x1 convolutional layer to allow for any size input image without losing positional information. As a result, the entire network is composed of convolutional layers, and by eliminating the fully connected layer, the network is not limited by the size of the input image. It can maintain the location information of the input image. The number of heatmaps obtained after going through the convolution layers equals the number of trained classes, with each heatmap representing one class.

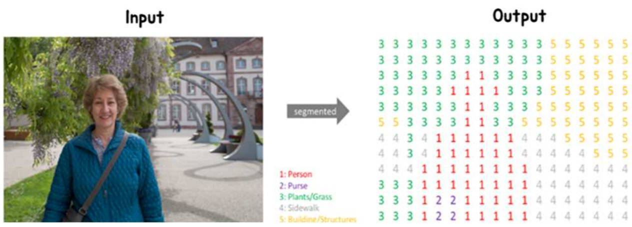

Fig. 3 Segmentation Map

The approximate heat maps corresponding to each class are increased to the original size through upsampling, and the upsampled heat maps are synthesized to create the final segmentation map as shown in Fig. 3 above. In other words, the class with the highest probability for each pixel is selected. By using the features of the FCN model, this study realized a function that can improve children's traffic safety awareness and prevent jaywalking by notifying them of the type of road they are looking at [21], [22], [23].

As input data from the camera module, the classes of each pixel can be identified through semantic segmentation technology. The judgment area is selected, and the highest class in the area is calculated to determine the type of road the child is looking at [24], [25].

The area for judging the type of road the child is looking at is divided into 5x5 by the width and height of the input data, as shown in Fig. 4, and the (5, 3) position is set as the judgment area. The reason for setting this position is that the (5, 3) position of the input data is the most accurate position to determine the type of road in advance, so the (5, 3) position is set as the judgment area. Fig. 4 shows an arbitrary class for better understanding. The class per pixel found through semantic segmentation is stored as a matrix, and the class that occupies most of the class values stored in the matrix in the (5, 3) area is used to judge the type of road where the child is looking.

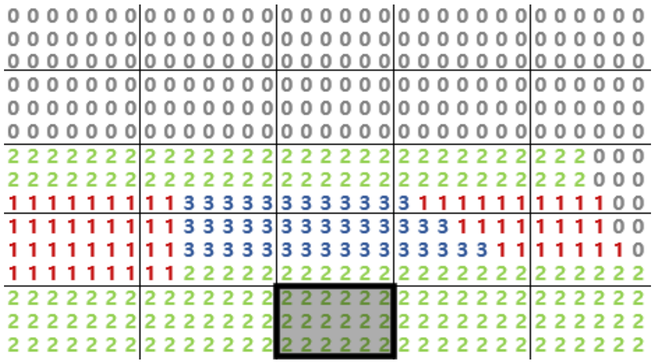

Fig. 4 Judgment Area Set

3) User Interface: Fig. 5 shows the app's main screen for parents. Click the Manage Safe Zone button on the leftmost side of the main screen to add or delete a child's safe zone. You can also view your child's jaywalking history.

Fig. 5 App for parents

Other features include the ability to add and delete safe zones when a child leaves a safe zone [26], [27], [28]. When a child leaves a safe zone, the parent is notified via the parent app, and the path the child took is marked with a red line. Newly reddened routes as a safe zone can be added or deleted [29], [30].

Fig. 6 Jaywalking History

Fig. 6 above shows a screen to view your child's jaywalking history. When a child jaywalks, the location information is stored on the server, and the parent app shows where and when the child jaywalked [31]. We have implemented a feature that allows parents to set alarms with their voice, allowing for contextual alerts when children are in dangerous locations.

C. *Anomaly Path Detection*

1) WAS Server Structure: Fig. 7 is the server structure diagram above. Nginx was used as a web server to perform HTTP communication with the child smart badge, and Django rest framework was used as an application framework to design a REST-style server because the child smart badge transmits real-time location information to the server. We used Gunicorn WSGI for the middleware, which is highly compatible with Nginx and Django. Gunicorn is deployed with Nginx in a reverse proxy configuration and passes requests and responses between Nginx and the Django framework.

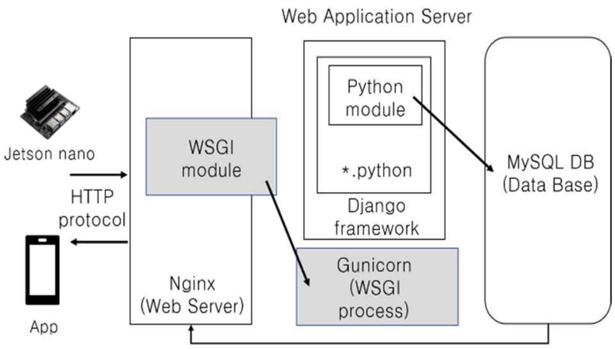

Fig. 7 Server Configuration

The server's DB (Data Base) is MySQL DB. The server's DB table is shown in Fig. 8 above. The DB stores the serial number of the child smart badge and the user's unique ID value in the users' table, which stores user information for running the child smart badge. The stored user information is used in the authentication process when the application requests data. The voice file table stores files that parents have recorded contextual notifications from the application. The GPS route, jaywalking, and new route tables store GPS information to ensure children's walking safety and prevent missing accidents.

```
+---------------------------+
| Tables_in_dbsmartbadge    |
+---------------------------+
| smartbadge_gpsroute       |
| smartbadge_jaywalking     |
| smartbadge_location       |
| smartbadge_newroute       |
| smartbadge_users          |
| smartbadge_voicefile      |
+---------------------------+
```

Fig. 8 Server DB Table

2) Analyzing GPS Information and Detecting Leaving the Safety Zone: The Child Smart Badge transmits real-time GPS information to the server. The GPS information sent to the server is stored in a separate DB, as it is necessary to set up the initial safe zone if no safe zone has been created.

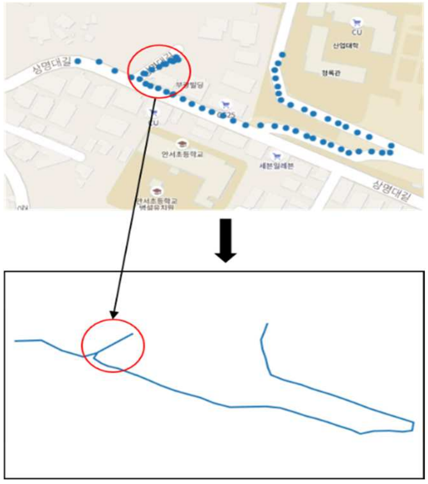

Fig. 9 Create safe zone Poly Line

The safety zones are created based on GPS information stored separately at the time of creation. After removing redundant and unnecessary information, as shown in Fig. 9, they are saved as PolyLine objects [35]. The safety zone saved as a PolyLine can be visualized and displayed in the parental application [35], [36].

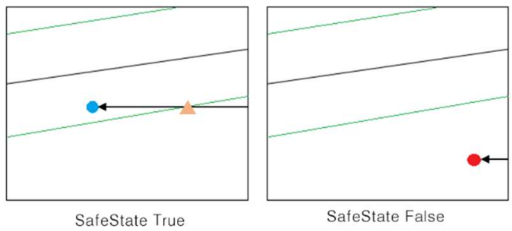

Fig. 10 Ray Casting Algorithm

For safe zone out-of-zone detection, the process of converting the saved safe zone PolyLine object to a Polygon object with a specific range is performed first. Then, when the server receives the real-time GPS information of the child's smart badge, the Ray Casting [37] algorithm is performed to detect the safe zone departure by determining that the GPS information is inside the safe zone when the number of intersections is odd as shown in Fig. 10 and returning the safe state as True, and outside the safe zone when the number of intersections is 0 or even.

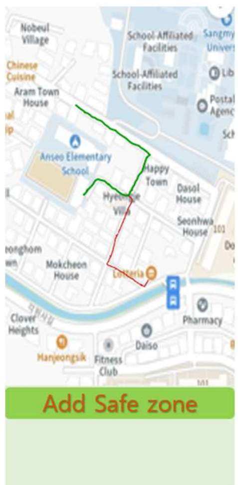

Fig. 11 Add Safe zone

If the safe zone is left, the GPS information is stored in the DB from the point of departure. The GPS information can then be added or deleted to the existing safe zone. In the case of addition, the safe zone is updated by finding the closest point to the PolyLine object of the existing safe zone and performing the same algorithm as creating the safe zone.

III. Results and Discussion

A. Experiment

The experimental environment was conducted within a limited area, and the smart badge was attached to the chest arm according to the average height (about 135 cm) of children in lower grades (1-3), as shown in Fig. 12 below. The first experiment was conducted at around 13:00 on a sunny day and the second at around 16:00 on a cloudy day.

Fig. 12 Children's smart badge attachment

Depending on the type of roadway the child is looking at, we experimented with detecting when the child is looking at a sidewalk, crosswalk, or driveway and when the child is looking at a temporary 2-kilometer safe zone.

B. Build Experimental Data

As shown in Fig. 13, there are four classes in total. To build the experimental data before semantic segmentation, we categorized the classes into background, roadway, sidewalk, and crosswalk according to the experimental environment.

Fig. 13 Class Information

Fig. 14 Screen Shot of Labelme

Fig. 14 above is a screenshot of Labelme. Labelme divides the image for training data into regions for each class and labels them.

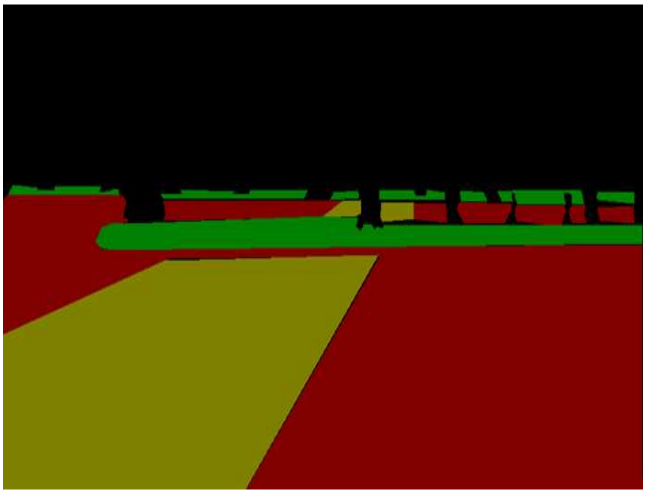

Fig. 15 Mask image obtained using Labelme

After labeling with Labelme, you can get a mask image, as shown in Fig. 15 above. To train the model, we built a training dataset of 300 images and a validation dataset of 75 images that distinguish between background, roadway, sidewalk, and crosswalk.

C. Experimental Results

1) Experiments based on the type of road the child is looking at.

The values in Table 1, Table 2, and Table 3 below represent the class number. As shown in Fig. 14, they represent the background, roadway, sidewalk, and crosswalk in order from 0 to 3. In Table 4, o and x indicate whether jaywalking is detected correctly or not.

a. Facing a sidewalk

In the case of sidewalks, if the judgment area is considered a sidewalk, as shown in Fig. 16, the child is considered walking safely on the sidewalk, and no notification is sounded. We conducted two experiments ten times each with 30 seconds of walking on the sidewalk in the experimental environment area, and the results are shown in Table 1.

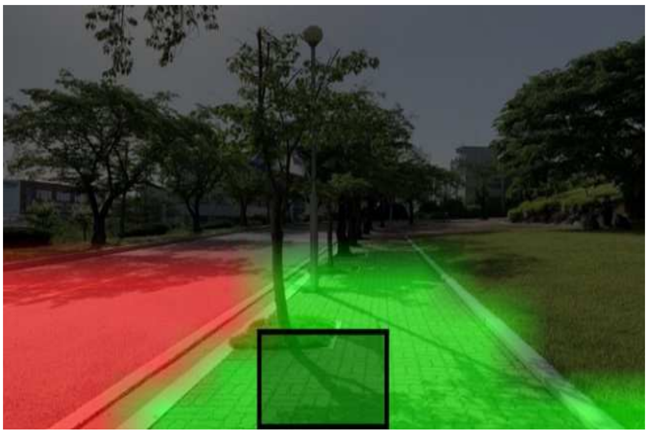

Fig. 16 Segmentation results when facing Sidewalk

TABLE I

WALKING SAFELY ON THE SIDEWALK

Count	1	2	3	4	5	6	7	8	9	10
1st	2	2	2	2	2	0	2	2	2	2
2nd	2	2	2	2	2	2	2	2	2	2

b. Facing a Crosswalk

In the case of crosswalks, if the judgment area is judged to be a crosswalk, as shown in Fig. 17, the child is deemed to be in front of the crosswalk, and a voice notification from the parent (e.g., "00, look both ways when the light is green and stop when the light is red!") sounds. The experiment results are shown in Table 2, based on the crosswalks in the experimental environment area, ten times in two situations.

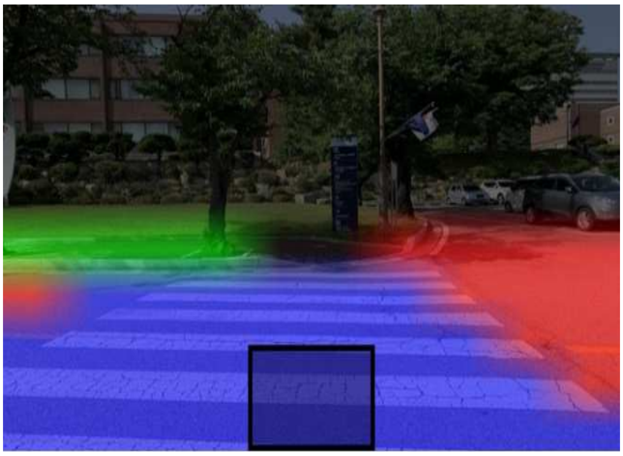

Fig. 17 Segmentation results when facing Crosswalk

TABLE II

FACING A CROSS WALK

Count	1	2	3	4	5	6	7	8	9	10
1st	3	3	3	1	3	3	3	3	3	3
2nd	3	3	3	3	3	3	3	1	3	3

c. Facing Roadway

In the case of a roadway, if the judgment area is judged to be a roadway, as shown in Fig. 18, it is judged that the child is walking toward the roadway and it is dangerous, and the parent's voice notification (e.g., "00, it is dangerous to run on the road, cross the crosswalk") sounds. When we conducted two experiments ten times each based on crosswalks in the experimental environment area, the results were as shown in Table 3.

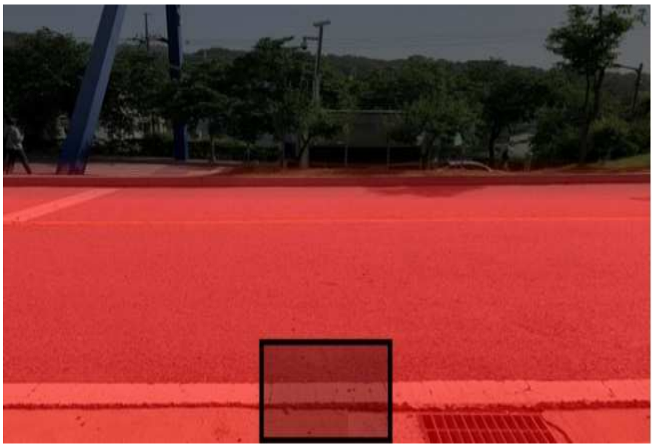

Fig. 18 Segmentation results when facing Roadway

TABLE III

FACING ROADWAY

Count	1	2	3	4	5	6	7	8	9	10
1st	1	1	1	1	1	1	1	1	1	1
2nd	1	1	1	1	1	1	1	1	1	1

d. When Detecting Jaywalking

In the case of jaywalking, if a certain amount of change in the acceleration sensor is detected after the judgment area is judged to be a roadway, as in 3.1.3, the child is considered to be attempting to jaywalk in the direction of the roadway. The parent's voice notification (e.g., "00, no jaywalking! Cross the crosswalk") sounds. The following results are shown in Table 4., which shows the results of two experiments with 10 cases of moving while facing the road in the experimental environment area.

2) Experiments with detecting out-of-zone behavior

For the experiment on detecting safe zone departure, we used a pre-generated 2-kilometer safe zone. The outcome was judged by whether the parental app received a notification of leaving the safe zone. We performed two sets of 10 exits for the Safe Zone Exit experiment. The methodology was moving the child's smart badge outside the safe zone. The results of the experiment are shown in Table 5 below.

TABLE IV

EXISTING SAFE ZONE

Count	1	2	3	4	5	6	7	8	9	10
1st	0	0	0	0	0	0	0	0	0	0
2nd	0	0	0	0	0	0	X	0	0	0

3) Analyzing the results

The experiment's results, depending on the type of road the child was looking at, were as follows: First, when the child looked at the sidewalk, it was recognized as a Background due to landscaping and installations other than the sidewalk. However, since the algorithm performs the same algorithm for Background for the sidewalk, no alerts were triggered, and the experiment proceeded without any problems. Second, there were two cases where the crosswalk was recognized as a road due to the black part of the crosswalk except for the white painted part. This could be improved by taking more photos of the crosswalk from different angles and training additional data to improve accuracy. Third, in the case of facing the roadway and detecting jaywalking, the notification worked correctly without any false recognition in 20 experiments. As such, it was possible to detect road conditions with an accuracy of more than 90% to perform child pedestrian safety, and it is expected to prevent child traffic accidents by effectively notifying children of dangerous situations with a guardian's recorded notification voice.

The experiment's results in detecting the departure from the safe zone were affected by the performance problem of the GPS module in the second cloudy weather, which caused the GPS not to receive the location information. Except for the case where the GPS module does not receive location information due to performance issues, it successfully detects the departure of the safe zone. It sends a safe zone departure notification to the guardian. By replacing the GPS module with a high-performance GPS module, it can be expected to prevent missing accidents more accurately.

IV. Conclusion

In this study, we proposed a method for detecting road type, creating a safe zone, and detecting deviation using a camera and GPS module on the Jetson Nano. Semantic segmentation was used to distinguish the types of roads and to notify children of road dangers in advance. GPS information based on the child's travel route was analyzed to create a safe zone and detect deviation. The app and server for parents communicate with the child's smart badge, record the parent's voice for various notifications, and receive notifications when the child strays.

We confirmed the proposed system's stability and accuracy through experiments and showed that it could detect children's walking safety and safety zone departure in real-time. This system can be utilized to prevent child accidents. Based on this research, we will continue to build more video datasets to improve the accuracy of semantic segmentation studies on how to directly prevent jaywalking and estimate the path of children's movement in real-time to analyze the risk of abnormal paths in advance.

Acknowledgment

This research was funded by a 2024 research Grant from Sangmyung University.

References

[1] E. C. S. Silva et al., "The Effect of Educational Intervention Regarding the Knowledge of Mothers on Prevention of Accidents in Childhood," *The Open Nursing Journal*, vol. 10, no. 1, pp. 113–121, Jul. 2016, doi:10.2174/1874434601610010113.

[2] T. İnce, S. Yalçın, and K. Yurdakök, "Parents' Attitudes And Adherence to Unintentional Injury Prevention Measures in Ankara, Turkey," *Balkan Medical Journal*, Feb. 2017, doi:10.4274/balkanmedj.2016.1776.

[3] Y. Cao, J. Wen, and L. Ma, "Tracking and collision avoidance of virtual coupling train control system," *Future Generation Computer Systems*, vol. 120, pp. 76–90, Jul. 2021, doi:10.1016/j.future.2021.02.014.

[4] C. Han et al., "Re-ID Driven Localization Refinement for Person Search," *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, Oct. 2019, doi: 10.1109/iccv.2019.00991.

[5] D.-Y. Park, K.-K. Yoo, and W.-S. Choi, "Effects of LED Safety Induction Block on Crosswalk Accident," *Journal of the Korea Academia-Industrial cooperation Society*, vol. 15, no. 7, pp. 4634–4643, Jul. 2014, doi: 10.5762/kais.2014.15.7.4634.

[6] J.-Y. Ryu and T.-S. Song, "Design and Implementation for Child Tracking System using GPS and WiFi under Android Environment," *Journal of the Korea Institute of Information and Communication Engineering*, vol. 18, no. 6, pp. 1343–1349, Jun. 2014, doi:10.6109/jkiice.2014.18.6.1343.

[7] S. Agrawal, S. Bhanderi, S. Amanagi, K. Doycheva, and G. Elger, "Instance Segmentation and Detection of Children to Safeguard Vulnerable Traffic User by Infrastructure," *Proceedings of the 9th International Conference on Vehicle Technology and Intelligent Transport Systems*, pp. 206–214, 2023, doi:10.5220/0011825400003479.

[8] S. Minaee, Y. Y. Boykov, F. Porikli, A. J. Plaza, N. Kehtarnavaz, and D. Terzopoulos, "Image Segmentation Using Deep Learning: A Survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, pp. 1–1, 2021, doi: 10.1109/tpami.2021.3059968.

[9] T. Zhou, W. Wang, E. Konukoglu, and L. Van Goo, "Rethinking Semantic Segmentation: A Prototype View," *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 2572–2583, Jun. 2022, doi: 10.1109/cvpr52688.2022.00261.

[10] Y. Yu et al., "Techniques and Challenges of Image Segmentation: A Review," *Electronics*, vol. 12, no. 5, p. 1199, Mar. 2023, doi:10.3390/electronics12051199.

[11] H.-J. Kang, "A Study on Analysis of Intelligent Video Surveillance Systems for Societal Security," *Journal of Digital Contents Society*, vol. 17, no. 4, pp. 273–278, Aug. 2016, doi:10.9728/dcs.2016.17.4.273.

[12] S. Iftikhar, Z. Zhang, M. Asim, A. Muthanna, A. Koucheryavy, and A. A. Abd El-Latif, "Deep Learning-Based Pedestrian Detection in Autonomous Vehicles: Substantial Issues and Challenges," *Electronics*, vol. 11, no. 21, p. 3551, Oct. 2022, doi:10.3390/electronics11213551.

[13] J. A. Antonio and M. Romero, "Pedestrians' Detection Methods in Video Images: A Literature Review," *2018 International Conference on Computational Science and Computational Intelligence (CSCI)*, Dec. 2018, doi: 10.1109/csci46756.2018.00074.

[14] Y. Zhu, J. Yang, X. Xieg, Z. Wang, and X. Deng, "Long-distanceinfrared video pedestrian detection using deep learning and backgroundsubtraction," *Journal of Physics: Conference Series*, vol. 1682, no. 1, p. 012012, Nov. 2020, doi: 10.1088/1742-6596/1682/1/012012.

[15] Y. Zhang, Y. Jin, J. Chen, S. Kan, Y. Cen, and Q. Cao, "PGAN: Part-Based Nondirect Coupling Embedded GAN for Person Reidentification," *IEEE MultiMedia*, vol. 27, no. 3, pp. 23–33, Jul. 2020, doi: 10.1109/mmul.2020.2999445.

[16] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. CVPR 2001, vol. 1, pp. I-511-I–518, doi: 10.1109/cvpr.2001.990517.

[17] X. Zhang, T. Wang, J. Qi, H. Lu, and G. Wang, "Progressive Attention Guided Recurrent Network for Salient Object Detection," *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Jun. 2018, doi: 10.1109/cvpr.2018.00081.

[18] J. Long et al., "Fully convolutional networks for semantic segmentation", *Proc. Conf. Comput. Vis. Pattern Recognit.*, pp. 3431-3440, 2015.

[19] S. Iftikhar, M. Asim, Z. Zhang, and A. A. A. El-Latif, "Advance generalization technique through 3D CNN to overcome the false positives pedestrian in autonomous vehicles," *Telecommunication Systems*, vol. 80, no. 4, pp. 545–557, Jun. 2022, doi: 10.1007/s11235-022-00930-1.

[20] S. Hartini, Z. Rustam, and R. Hidayat, "Designing Hybrid CNN-SVM Model for COVID-19 Classification Based on X-ray Images Using LGBM Feature Selection," *International Journal on Advanced Science, Engineering and Information Technology*, vol. 12, no. 5, pp. 1895–1906, Sep. 2022, doi: 10.18517/ijaseit.12.5.16875.

[21] L. Chen et al., "Survey of pedestrian action recognition techniques for autonomous driving," *Tsinghua Science and Technology*, vol. 25, no. 4, pp. 458–470, Aug. 2020, doi: 10.26599/tst.2019.9010018.

[22] A. S. Putra and H. L. H. S. Warnars, "Intelligent Traffic Monitoring System (ITMS) for Smart City Based on IoT Monitoring," *2018 Indonesian Association for Pattern Recognition International Conference (INAPR)*, pp. 161–165, Sep. 2018, doi:10.1109/inapr.2018.8626855.

[23] N. A. Khan, N. Z. Jhanjhi, S. N. Brohi, R. S. A. Usmani, and A. Nayyar, "Smart traffic monitoring system using Unmanned Aerial Vehicles (UAVs)," *Computer Communications*, vol. 157, pp. 434–443, May 2020, doi: 10.1016/j.comcom.2020.04.049.

[24] L. F. P. de Oliveira, L. T. Manera, and P. D. G. D. Luz, "Development of a Smart Traffic Light Control System with Real-Time Monitoring," *IEEE Internet of Things Journal*, vol. 8, no. 5, pp. 3384–3393, Mar. 2021, doi: 10.1109/jiot.2020.3022392.

[25] A. Hilmani, A. Maizate, and L. Hassouni, "Automated Real-Time Intelligent Traffic Control System for Smart Cities Using Wireless Sensor Networks," *Wireless Communications and Mobile Computing*, vol. 2020, pp. 1–28, Sep. 2020, doi: 10.1155/2020/8841893.

[26] F. Ali, A. Ali, M. Imran, R. A. Naqvi, M. H. Siddiqi, and K.-S. Kwak, "Traffic accident detection and condition analysis based on social networking data," *Accident Analysis & Prevention*, vol. 151, p. 105973, Mar. 2021, doi: 10.1016/j.aap.2021.105973.

[27] L. Hu, J. Ou, J. Huang, Y. Chen, and D. Cao, "A Review of Research on Traffic Conflicts Based on Intelligent Vehicles," *IEEE Access*, vol. 8, pp. 24471–24483, 2020, doi: 10.1109/access.2020.2970164.

[28] M. Saleem, S. Abbas, T. M. Ghazal, M. Adnan Khan, N. Sahawneh, and M. Ahmad, "Smart cities: Fusion-based intelligent traffic congestion control system for vehicular networks using machine learning techniques," *Egyptian Informatics Journal*, vol. 23, no. 3, pp. 417–426, Sep. 2022, doi: 10.1016/j.eij.2022.03.003.

[29] S. Dhingra, R. B. Madda, R. Patan, P. Jiao, K. Barri, and A. H. Alavi, "Internet of things-based fog and cloud computing technology for smart traffic monitoring," *Internet of Things*, vol. 14, p. 100175, Jun. 2021, doi: 10.1016/j.iot.2020.100175.

[30] J. Bharadiya, “Artificial Intelligence in Transportation Systems A Critical Review,” *American Journal of Computing and Engineering*, vol. 6, no. 1, pp. 34–45, Jun. 2023, doi: 10.47672/ajce.1487.

[31] W.-H. Lee and C.-Y. Chiu, “Design and Implementation of a Smart Traffic Signal Control System for Smart City Applications,” *Sensors*, vol. 20, no. 2, p. 508, Jan. 2020, doi: 10.3390/s20020508.

[32] B. Wang et al., “Automatic Fault Diagnosis of Infrared Insulator Images Based on Image Instance Segmentation and Temperature Analysis,” *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 8, pp. 5345–5355, Aug. 2020, doi:10.1109/tim.2020.2965635.

[33] X. Cao, S. Guo, J. Lin, W. Zhang, and M. Liao, “Online tracking of ants based on deep association metrics: method, dataset and evaluation,” *Pattern Recognition*, vol. 103, p. 107233, Jul. 2020, doi:10.1016/j.patcog.2020.107233.

[34] X. Chen, Y. Duan, R. Houthooft, J. Schulman, I. Sutskever and P. Abbeel, "InfoGAN: Interpretable representation learning by information maximizing generative adversarial nets", *Proc. 30th Int. Conf. Neural Inf. Process. Syst*., pp. 2180-2188, 2016.

[35] S. Ahmed, R. K. Chakrabortty, D. L. Essam, and W. Ding, “Poly-linear regression with augmented long short term memory neural network: Predicting time series data,” *Information Sciences*, vol. 606, pp. 573–600, Aug. 2022, doi: 10.1016/j.ins.2022.05.078.

[36] M. A. Castán-Lascorz, P. Jiménez-Herrera, A. Troncoso, and G. Asencio-Cortés, “A new hybrid method for predicting univariate and multivariate time series based on pattern forecasting,” *Information Sciences*, vol. 586, pp. 611–627, Mar. 2022, doi:10.1016/j.ins.2021.12.001.

[37] M. S. Kim, “Vehicle entry/exit detection technique using Ray Casting Algorithm,” *M.S. thesis*, Dept. Knowledge and Information Engineering, Ajou Univ., Suwon, Korea, 2017.