ISSN: 2994-6433

Review Article

Journal of Sensor Networks and Data Communications

A Hybrid System Combining the Shortest Path Algorithm with and Real-Time VGG19 Convolutional Neural Network

Imen Chebbi[1*], Sarra Abidi[2,3] and Leila Ben Ayed[3]

[1]*FSEG Sfax, University Sfax, Tunisia*

[2]*RIADI Laboratory, University of Manouba, Tunisia*

[3]*ENSI, University of la Manouba, Tunisia*

[*]Corresponding Author
Imen Chebbi, FSEG Sfax, University Sfax, Tunisia.

Submitted: 2024, Jul 15; **Accepted**: 2024, Aug 14; **Published**: 2024, Aug 19

Citation: Chebbi, I., Abidi, S., Ayed, L. B. (2024). A Hybrid System Combining the Shortest Path Algorithm with and Real-Time VGG19 Convolutional Neural Network. *J Sen Net Data Comm, 4*(2), 01-07.

Abstract

In the aftermath of catastrophic natural catastrophes such as earthquakes, tsunamis, and explosions, providing immediate help to key areas can mean the difference between life and death for many individuals. To meet this critical demand, we created a hybrid transportation system that harnesses the power of vgg19 and traditional shortest path algorithms. The objective was to create a real-time system that could address these issues and provide a novel viewpoint. The suggested approach can precisely anticipate damaged roads and steer clear of them when determining the shortest way between sites during emergencies or natural disasters by merging VGG19 with the shortest path algorithm. With the potential to save many lives, this creative strategy can assist emergency responders reach vital places swiftly and effectively while also saving important time and resources. The experimental study shows that the proposed model can achieve robust results. In fact, our solution achieves 98% accuracy rate and a 0.972 G-Mean score on the test set.

Keywords: Artificial Intelligence, Convolutional Neural Network (CNN), Shortest Path, VGG19, Road Damage Detection

1. Introduction and Motivation

Numerous domains, including autonomous cars, mobile robot groups, multi-robot systems, and intelligent robot design, have expressed interest in the integration of real-time convolutional neural networks (CNN) with shortest path methods. In order to perform real-time environment perception utilizing real sensor data, Jahromi et al. suggested a hybrid multi-sensor fusion architecture for perception in autonomous cars [1]. Likewise, Medvedev and associates employed neural networks to provide both the shortest and safest path planning algorithms when focusing on path planning for a group of drones [2]. Liao et al. presented a fuzzy ensemble technique with deep learning in the setting of multi-robot systems, integrating the shortest path quicker algorithm to promote agent information exchange [3]. Additionally, Chang et al. combined neural networks, path planning, fuzzy theory, and image processing to create an outdoor patrol robot [4]. They then used the Dijkstra and Ant algorithms to determine the shortest paths for their patrol jobs. The research of Rajamohana et al. shows that hybrid systems are not just used in robotics on the combined use of CNN and Bidirectional Long Short Term Memory (BiLSTM) for driver sleepiness detection [5]. Furthermore, Tang et al. surpassed the conventional SA algorithm, Hopfield neural network, and genetic algorithm in generating the shortest path by the development of an enhanced hybrid algorithm that combines the two techniques for path optimization [6]. Furthermore, Lee et al. presented a lightweight UNet architecture that integrates a route prediction algorithm with CNN for real-time performance evaluation, enabling end-to-end learning of lane detection and path prediction in autonomous driving [7]. Singh and others highlighted the significance of real-time sensor data and evacuation path support in their hybrid architecture that used LoRa and Zigbee for real-time fire evacuation path implementation [8]. The significance of effective path planning and decision-making processes in dynamic environments is highlighted by the overall promising results of integrating real-time CNN with shortest path algorithms in hybrid systems, which have been applied to a variety of applications, from autonomous vehicles to fire evacuation systems.

In this work, the traditional shortest path method was combined with cutting-edge artificial intelligence algorithms, namely Convolutional Neural Networks (CNN), in an attempt to overcome the shortcomings of previous approaches. The objective was to create a real-time system that could address these issues and provide a novel viewpoint. The suggested approach can precisely anticipate damaged roads and steer clear of them when determining the shortest way between sites during emergencies or natural disasters by merging CNN with the shortest path algorithm. With the potential to save many lives, this creative strategy can assist emergency responders reach vital places swiftly and effectively while also saving important time and resources. Due to its ability to speed up emergency action, the automatic identification of roadways rendered unusable by natural catastrophes might potentially save countless lives. In order to accomplish this goal, we used the Convolutional Neural Network (CNN) technique in this study to automatically identify roadways that have become unsuitable for whatever reason. Afterwards, a real-time CNN-integrated shortest route method was created by combining this approach with the shortest path algorithm, which finds the shortest distance between two sites. The core idea of the proposed framework, which is depicted in Figure 1, is to use CNN to forecast damaged roads and then steer clear of them while utilizing the shortest path algorithm to discover the shortest route between two places. This strategy has the potential to save many lives by significantly increasing the effectiveness and speed of emergency response operations during natural catastrophes. The basic idea behind the suggested hybrid system is to assess road conditions after natural disasters, such earthquakes, by deploying unmanned aerial vehicles or already-existing CCTV camera systems. The shortest path algorithm adjusts in real-time based on these evaluations, enabling emergency personnel to promptly adjust to last-minute route changes and hasten their arrival at vital sites.

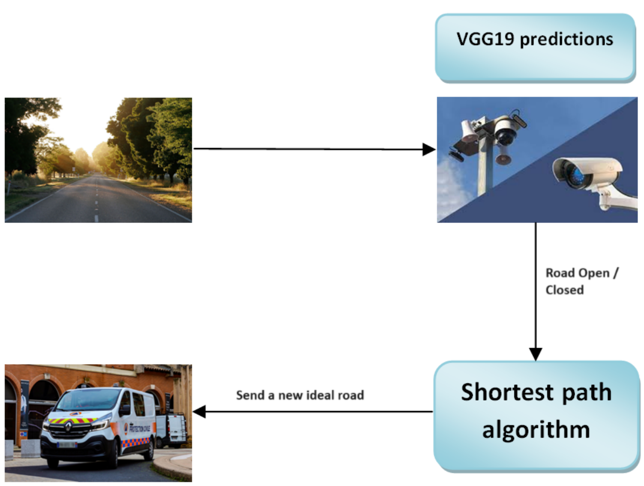

Figure 1: The Core Idea of the Proposed Framework

The rest of this paper is organized as follows. Section 2 presents Preliminary Concepts. Section 3 describes the Literature review. Section 4 presents our approach. Section 5 presents Dataset Description. Section 6 Evaluation and Discussion. Section 7 outlines conclusions and future lines of work.

2. Preliminary Concepts

In order to find the shortest route, a hybrid system that combines the convolutional neural network (CNN) and shortest path method has been presented for real-time applications in this study. In order to offer a more thorough comprehension of this system's operation, the ensuing subsections expound on the employed approaches and dataset.

2.1. Convolutional Neural Network (CNN)

A CNN is one type of neural network that has the ability to automatically identify and categorize the distinct features of the neural network. This deep learning method applies learnable weights and biases to its features by using a feedforward network, which implies that it receives an input. The final output is generated by the non-linear activation function of each neuron in this artificial neural network. Several nearby linked neurons come together to create a kernel, also known as a weight matrix. Each of the several kernels that make up a "convolution layer" (CONV) generates an output. Convolution operations are performed by the CONV layer as it scans an input. It does this by utilizing its many hyper-parameters, which can affect how well a model trains and are pre-set prior to the learning process. These hyper-parameters include the stride, which defines the number of pixels by which the window moves following each operation, and the filter size, which denotes the size of a filter that is applied during the process. The resulting output is a feature map, often known as an activation map. The pooling layer (POOL), a down sampling technique that gathers the maximum and average values of a specific region while implementing some spatial invariance, is the next processing step in the chain. After obtaining these values, the network moves on to the fully connected layer (FC), where each neuron is connected to every input. An image vector with a set of contained characteristics is a typical CNN input. After passing through each of these stages, the image vector produces a probabilistic approximation that is capable of identifying the target image. This method's main advantage over other classification methods is that it requires a lot less preprocessing on a traditional CNN. The CNN organizational chart is displayed in Figure 2.

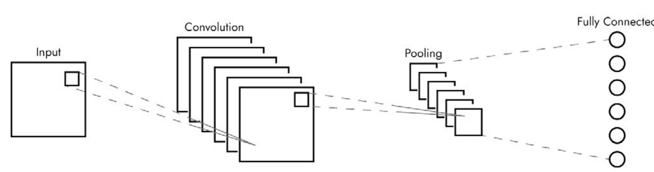

Figure 2: The Structure of a CNN

2.2. Transfer Learning

Machine learning has shown successful in several sectors, yet most models specialize at a specific task. When faced with a new assignment, retraining the model and gathering sufficient data may prove difficult. As a result, transfer learning is a popular method for achieving high-quality results in such instances. Transfer learning aims to apply information from one domain to another [9]. To demonstrate this method, take the following example: Two individuals want to learn how to play the piano.

Individuals with prior guitar experience may find it easier to learn piano [10]. This demonstrates how information from one domain may be used to another. Transfer learning, which applies a model learned on large datasets to smaller ones, is highly effective and offers several benefits [11]. The analysis favors transfer learning due to insufficient data samples. The goal is to improve results with minimal data by leveraging transfer learning's benefits instead of training from scratch. Using a pre-trained network with optimum weights for deep learning in limited datasets is a frequent and efficient practice. Numerous pre-trained CNN architectures are available in the literature, including AlexNet, VGG16, InceptionV3, and ResNet50 [12-15]. These architectures were trained using sizable data sets, such as ImageNet, and they yield state-of-the-art performance for computer vision applications [16]. Using such networks, which have been trained on large amounts of data, has the main advantage that they have already learned hidden patterns of images from many categories. As an example, the ImageNet database has 5247 categories and 3.2 million photos. As a result, the acquired information can be easily applied to images of different categories in a different area.

1. VGG-19 Model: Simonyan and Zisserman from Oxford University created the VGG19 model, a 19-layer CNN (3 fully linked, 16 convolution) that only employed 3 * 3 filters along pad and stride of 1 and 2 * 2 layers max pooling along stride 2. In contrast to AlexNet, VGG19 (as seen in Figure 3) is a more sophisticated CNN with more layers. Little 3 * 3 filters are utilized in each convolutional layer of these deep networks to reduce the number of parameters, and they are highly effective with an error rate of 7.3%. Even though this model did not win the ILSVRC 2014, the VGG Net is one of the most influential publications since it supported the notion that CNNs will eventually acquire a deep network of layers.

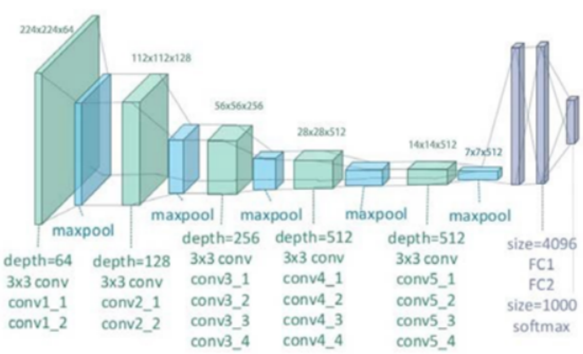

Figure 3: The Architecture Network of VGG-19 Model [17]

2.3. Shortest Path Algorithm

In many different domains, including transportation, communication, and route planning, where figuring out the shortest path between a starting point and a destination might be crucial for optimizing advantages, the shortest path technique is frequently applied (see Figure 4). Graph theory forms the basis of the mathematical model for the shortest path, which is used in situations where minimizing the distance between two nodes that represent the possible paths is the goal. An integer linear programming problem can be used to express this model. We can create an optimization problem to discover the shortest path given a directed network with weights, a source (s), and a goal (w) V.

$$min \sum_{u,v} x_{uv} w_{uw} \tag{1}$$

Subject to:

$$\sum_{u} x_{su} - \sum_{v} x_{vs} = 1 \tag{2}$$

$$\sum_{u} x_{vt} - \sum_{u} x_{tu} = 1 \tag{3}$$

$$\sum_{q} x_{pq} - \sum_{r} x_{rp} = 0, for \forall \in V - \{s, t\} \tag{4}$$

$$x = 0 or 1 \tag{5}$$

where xi,j refers to the edge in the network, if it is in the shortest path, it takes one otherwise it takes zero, and w i,j is the weight for the corresponding edge.

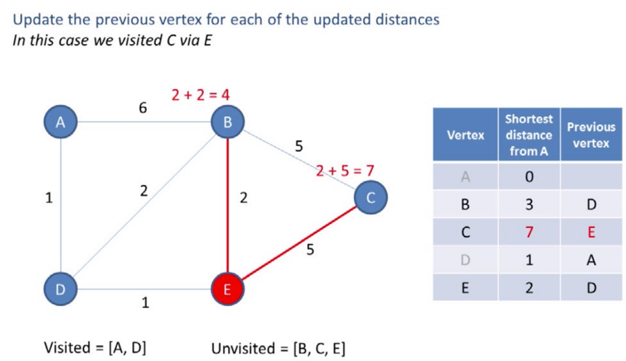

Figure 4: Shortest Path Algorithm

3. Literature Review

The incorporation of artificial intelligence methodologies into diverse domains has resulted in noteworthy progressions concerning prognostication and adjudication procedures. In their discussion of artificial neural networks and fuzzy graphoidal covering numbers for cancer diagnosis, Bhattacharya et al. emphasize the significance of integrating several approaches to provide reliable findings [18]. Comparably, Warnecke et al. highlight the advantages of merging several sensor systems for enhanced performance by emphasizing the use of multimodal signal fusion for reliable in-vehicle heartbeat detection [19]. Zhang et al. present a hardware acceleration design strategy based on SDSoC for processing efficiency in the field of real-time object classification [20]. The importance of optimization techniques in improving real-time object categorization performance is highlighted by this work. Moreover, the work of path planning algorithms in the autonomous driving system highlights the usage of Convolutional Neural Networks (CNN) for real-time object tracking, highlighting the efficiency of neural networks in processing visual data for navigational reasons [21]. In the literature, combining various neural network topologies has also been studied. In order to increase accuracy, a hybrid strategy combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) for histopathological categorization is presented in medical image analysis utilizing deep learning algorithms [22]. This technique highlights the advantages of integrating several neural network models. The use of CNN and LSTM in building a deep learning hybrid model for predicting aircraft trajectories is also covered in Aircraft Trajectory Prediction and Aviation Safety in ADSB Failure, emphasizing the benefits of combining spatial and temporal variables for precise predictions. Overall, the assessment of the literature shows that there is a growing trend in real-time processing and prediction tasks across multiple domains to combine different approaches, like neural networks and optimization strategies. Neural network integration is one area where artificial intelligence approaches show promise for enhancing complex system prediction accuracy and decision-making processes. According to this viewpoint, the study's objective is to use the VGG19 algorithm to categorize damaged routes that are no longer functional. The traditional shortest path technique is then used with this model to optimize the shortest path in real-time based on the VGG19 forecast. The objective of this methodology is to suggest a practical resolution for transportation networks that can function effectively in the aftermath of an unforeseen calamity.

4. Our Proposed Approach

Setting a new route to a destination without time constraints is simple. For example, a logistics company can evaluate road conditions a day in advance and select the best route to avoid any road closures. However, in other circumstances, there may be a very short period of time to find an alternative path. In these situations, a new approach to reconstructing the model that finds the shortest path must be devised. For instance, a powerful earthquake may destroy the roads leading to important locations, causing traffic to stop. Rescue crews in these situations must act fast to find an alternate route to the impacted locations. They can reach the crucial spots more quickly and avoid any potential delays if this procedure moves more quickly. By using this method, we have integrated the shortest path algorithm with image processing. A real-time, AI-based camera system recognizes any damage on the road in the event of an earthquake that renders a roadway leading to a vital spot impassable. The problem is then classified and an estimate of whether the path is closed (1) or undamaged (0) is made using the VGG19 algorithms previously discussed. A basic sequence diagram representing the relationship in real-time between the shortest path method and VGG19 in a hybrid system is shown in Figure 5: In this diagram:

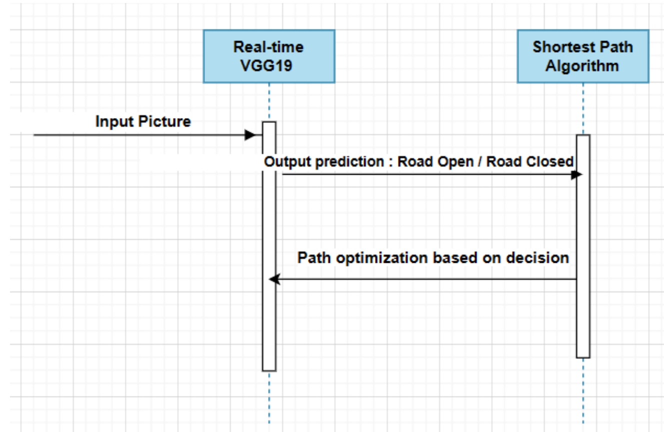

Figure 5: The Relationship in Real-Time between the Shortest Path Method and VGG19 in a Hybrid System

• The real-time VGG19 receives input data, such as images or sensor readings.
• The VGG19 processes the data and generates a prediction or output.
• The prediction is passed to the shortest path algorithm, which makes decisions based on this output.
• The shortest path algorithm optimizes a path or decision based on the VGG19's output.
• Finally, the optimized path or decision is returned for implementation or further action.

5. Dataset

In keeping with the purpose of this study, pictures of roads that were impassable because of natural disasters were collected, along with pictures of roads that did not provide a traffic hazard. Unexpected occurrences, like a natural disaster or accident, might cause even typically open highways to suddenly close. For example, heavy hurricanes or earthquake damage may render a frequently frequented street impassable, hindering the efforts of emergency personnel. These presumptions informed the collection of the data used in this investigation. When gathering the data, we made sure the roads were badly deteriorated to the point where it was impeding traffic. There were no pictures of roads with little fissures through which cars could still drive. There were 350 unique photos taken in all, 200 of which had damage and 150 of which were unharmed.

6. Evaluation and Discussion

A confusion matrix, which is a n × n matrix with n denoting the number of classes, is used to gauge how well the model performs on the classification task. Additionally, each entry in it displays the proportion of samples from class i that are allocated to class j. Table 1 shows that while CM is built for binary classes, it can be extended to many more.

		Class_pos	Class_neg
Actual	Class_pos Class_neg	True Positive (T P) False Negative (FN)	False Positive (FP) True Negative(TN)

Table 1: The Confusion Matrix (CM)

In Table 1, true positive (TP) denotes the amount of classpos data predicted that actually belongs to classpos, true negative (TN) denotes the amount of classneg data predicted that actually belongs to classneg, false positive (FP) denotes data predicted as classneg but actually belongs to classpos, and false negative (TN) denotes data predicted as classneg but actually belongs to classpos. We have also computed another evaluation metric utilizing the confusion matrix, which is dependent on the parameters of the confusion matrix. The three evaluation measures are mean, sensitivity, and specificity. In Equations 6, 7, and 8, their formulation is displayed.

$$Sensitivty = \frac{TP}{TP + FN} \tag{6}$$

$$Specificity = \frac{TN}{TN + FP} \tag{7}$$

$$GMean = \sqrt{Sensitivty * Specificity} \tag{8}$$

We provide a thorough examination of the CNN models that we chose in this section. The dataset we gathered was divided into three sets, as was previously indicated: 70% was used for training, 15% was used for testing, and 15% was used for validation. In order to make sure the selected models were not trainable, we also fixed every layer—aside from the output layer—and modified the output layer to match our dataset. There were two categories assigned to the training dataset: ”closed road” and ”open road.” The goal of providing a thorough study of the CNN methods' classification results is to assess their effectiveness in light of the predetermined standards, as this is essential to the hybrid strategy's effective execution. This section presents the results of computing the accuracy and other pertinent metrics for each approach using the test and development datasets. These analyses help us decide which CNN techniques to employ in the suggested system by shedding light on how well they work for the particular classification task at hand. Figure 6 presents VGG19 evaluation metrics, (a) training and validation loss, (b) confusion matrix, and (c) training and validation accuracy. One of the most important measures of a model's efficacy in machine learning is how well it performs on the test set. The performance of our technique on the test set, which consists of data that has never been seen before. Stated differently, this table shows the performance of the trained model on fresh datasets. As was previously indicated, the trained model was assessed on a test set of 30 distinct photographs, 13 of which had blocked roads and 17 of which had open roads, at a rate of 5%.

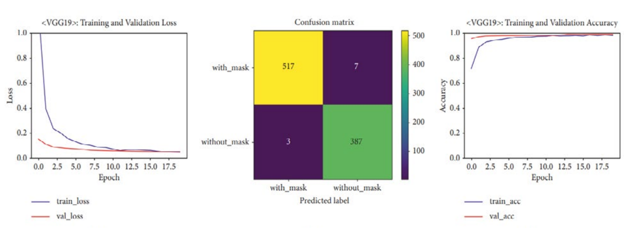

Figure 6: VGG-19 Evaluation Metrics, (a) Training and Validation Loss, (b) Confusion Matrix, and (c) Training and Validation Accuracy

Table 2 shows that the model performs remarkably well in terms of accuracy and loss values on the test set. In addition, the model showed excellent performance in various evaluation measures based on the estimated values in the test set. As shown in Table 3, the model's sensitivity, specificity, and G-Mean values were, respectively, 0.942, 1, and 0.9720. The model can correctly categorize data that belong to both classes, as evidenced by the high G-Mean score. Moreover, getting this score from the test set improves the model's dependability. The remarkable functionality of the model is critical to the effective operation of the hybrid system. Given that it is a crucial component needed to apply the updated shortest path algorithm previously stated, the high G-Mean score is very notable. Given the high G-Mean score and the model's correct predictions, it appears that the hybrid system can function quite accurately.

Loss and Accuracy Evaluation	Performance
Test Loss	0.074
Test Accuracy	0.980

Table 2: Performance of Model in Test Set

Evaluation Metrics	Performance
Sensitivity	0.942
Specificity	1
G-Mean	0.972

Table 3: Performance of Model in Terms of Sensitivity, Specificity, and G-Mean

We compare our approach here with several works that are worked on machine learning: Table 4 details the comparison of our best results with those obtained by other works in the literature. Figure 7 presents an accuracy comparison between the proposed model and other benchmark models, demonstrating that our model's accuracy is higher than the other models'. Table 4 presents an accuracy comparison between the proposed model and other models from the literature. It is evident from this comparison that the suggested model performs better than its peers, achieving an accuracy of 98%. Although more research is needed to compare our findings with those of the literature, the overall outcomes demonstrate the value of using our model to identify the optimal route. By using these techniques, one can maintain the results with those of other comparable works while somewhat reducing the performance gained.

Type	ACC(%)
OUR MODEL	98
Vadim Struk [23]	95
Yu et al. [24]	94.85
Dominguez et al. [25]	84
Dia [26]	95
ATOS 2012 [27]	93

Table 4: Comparison with other works available in the literature

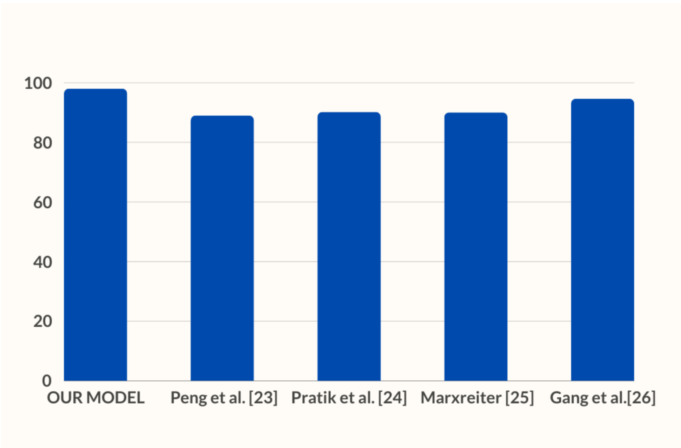

Figure 7: Comparison with other works available in the literature

7. Conclusion

The objective of this research was to create a hybrid system that would provide prompt access to vital locations in the event of a natural disaster. Predicting a road's usability and incorporating that prediction into the shortest path algorithm are the two main parts of this system. An image dataset comprising 350 pictures of both intact and damaged roads was gathered from multiple sources. Owing to the dataset's low size, training was done using a pre-trained VGG19 model. On the training, validation, and test sets, the model was able to obtain accuracy rates of 92%, 83%, and 72%, respectively. Furthermore, as Table 3 illustrates, it produced extremely positive outcomes in terms of sensitivity, specificity, and G-mean evaluation criteria. A drawback of the existing system is its restricted data set, which was lessened by the use of transfer learning. The system's objective is to optimize the shortest path algorithm in real-time. We think that this work could be used as a guide for the suggested system's future development. After a natural disaster, putting this concept into practice could greatly speed up emergency response times and save lives [23-27].

Ethical Statement

Conflict of interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Competing Interests

The authors declare that they have no competing interests.

Acknowledgements

We would like to express our sincere gratitude to RIADI laboratory that have contributed to the publication of this research paper.

Disclosures (financial and non-financial interests, funding)

No funding was received.

Author Contributions statement

The authors contributed equally to this work.

Research Data Policy and Data Availability Statements

Data sharing apply to this article because a dataset was generated and analyzed during the current study.

References

1. Shahian Jahromi, B., Tulabandhula, T., & Cetin, S. (2019). Real-time hybrid multi-sensor fusion framework for perception in autonomous vehicles. *Sensors, 19*(20), 4357.
2. Medvedev, M., & Pshikhopov, V. (2020). Path planning of mobile robot group based on neural networks. In *Trends in Artificial Intelligence Theory and Applications. Artificial Intelligence Practices: 33rd International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, IEA/AIE 2020, Kitakyushu, Japan, September 22-25, 2020, Proceedings 33* (pp. 51-62). Springer International Publishing.
3. Liao, P., Xu, M., & Yang, C. (2020). A fuzzy ensemble method with deep learning for multi-robot system. *IEEE Access, 8,* 220352-220363.
4. Chang, W. C., & Juang, J. G. (2021). Automatic Outdoor Patrol Robot Based on Sensor Fusion and Face Recognition Methods. *Applied Sciences, 1*1(19), 8857.
5. Rajamohana, S. P., Radhika, E. G., Priya, S., & Sangeetha, S. (2021). Driver drowsiness detection system using hybrid approach of convolutional neural network and bidirectional long short term memory (CNN_BILSTM). *Materials Today: Proceedings, 45*, 2897-2901.
6. Tang, S., Zhao, H., Wang, Z., Zhu, Y., Hou, D., & Wang, H. (2021). Analysis of the material distribution system of wise information technology of 120 under deep learning. *The Journal of Supercomputing, 77,* 9988-10002.
7. Lee, D. H., & Liu, J. L. End-to-end deep learning of Lane Detection and path prediction for real-time autonomous driving. arXiv 2021. *arXiv preprint arXiv:2102.04738.*
8. Singh, R., Birajdar, G. S., Rashid, M., Gehlot, A., Akram, S. V., AlGhamdi, A. S., & Alshamrani, S. S. (2021). Hybrid architectural network implementation to realize a fire evacuation path with 2.4 ghz zigbee and lora. *Sustainability, 13*(23), 13238.
9. Weiss, K., Khoshgoftaar, T. M., & Wang, D. (2016). A survey of transfer learning. *Journal of Big data, 3*, 1-40.
10. Pan, S. J., & Yang, Q. (2009). A survey on transfer learning. *IEEE Transactions on knowledge and data engineering, 22*(10), 1345-1359.
11. Ling, X., Dai, W., Xue, G. R., Yang, Q., & Yu, Y. (2008, August). Spectral domain-transfer learning. In *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 488-496).
12. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems, 25.*
13. Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556.*
14. Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the inception architecture for computer

vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2818-2826).
15. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).
16. Deng, J., Dong, W., Socher, R., Li, L. J., Li, K., & Fei-Fei, L. (2009, June). Imagenet: A large-scale hierarchical image database. In 2009 *IEEE conference on computer vision and pattern recognition* (pp. 248-255). Ieee.
17. Zheng, Y., Yang, C., & Merkulov, A. (2018, May). Breast cancer screening using convolutional neural network and follow-up digital mammography. In *Computational Imaging III* (Vol. 10669, p. 1066905). SPIE.
18. Bhattacharya, A., & Pal, M. (2024). Prediction on nature of cancer by fuzzy graphoidal covering number using artificial neural network. *Artificial Intelligence in Medicine, 148*, 102783.
19. Warnecke, J. M., Lasenby, J., & Deserno, T. M. (2023). Robust in-vehicle heartbeat detection using multimodal signal fusion. *Scientific Reports, 13*(1), 20864.
20. Zhang, B., Liu, Y., & Zhang, Y. (2023, October). Design of real-time object classification acceleration platform based on SDSoC. In *Fourth International Conference on Computer Science and Communication Technology (ICCSCT 2023)* (Vol. 12918, pp. 553-558). SPIE.
21. Reda, M., Onsy, A., Haikal, A. Y., & Ghanbari, A. (2024). Path planning algorithms in the autonomous driving system: A comprehensive review. *Robotics and Autonomous Systems, 174*, 104630.
22. Li, M., Jiang, Y., Zhang, Y., & Zhu, H. (2023). Medical image analysis using deep learning algorithms. *Frontiers in Public Health, 11,* 1273253.
23. Vadim Struk ”The Road Ahead: Trends and Applications of AI in Transportation”, ai-in-transportation, 2024.
24. Yu, M., Yang, P., & Wei, S. (2018, May). Railway obstacle detection algorithm using neural network. In *AIP Conference Proceedings* (Vol. 1967, No. 1). AIP Publishing.
25. Dominguez-Sanchez, A., Orts-Escolano, S., & Cazorla, M. (2017). Recognizing pedestrian direction using convolutional neural networks. In *Advances in Computational Intelligence: 14th International Work-Conference on Artificial Neural Networks, IWANN 2017, Cadiz, Spain, June 14-16, 2017, Proceedings, Part II 14* (pp. 235-245). Springer International Publishing.
26. Dia, H. (2001). An object-oriented neural network approach to short-term traffic forecasting. *European Journal of Operational Research, 131*(2), 253-261.
27. ATOS 2012. Expecting the Unexptected Business Pattern Management. Atos Scientific Community. Available online: https://atos.net/content/dam/global/ascent-whitepapers/ascentwhitepaper-expecting-the-unexpected-business-pattern-management.pdf (accessed on 2 October 2018).