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MODEL OF THE INTELLIGENT SYSTEM FOR PREDICTION OF ROAD TRAFFIC ACCIDENTS

*This study **aims** to determine the prerequisites for the occurrence of road traffic accidents, analyze the most dangerous maneuvers of motor vehicles that can lead to hazardous situations, and develop the most effective method for promptly informing the driver about potential danger. The **goal** of this study is to develop an information system that ensures timely notification of drivers about possible road traffic accidents in designated hazardous areas. The **tasks** include: investigating existing computer vision models for classification and object tracking tasks and determining the most suitable ones for deployment on a single-board computer Nvidia Jetson, while examining their performance and technical limitations; developing an optimized solution for the prompt notification of drivers about danger; creating an algorithm for detecting potential vehicle collisions that integrates computer vision methods and mathematical modeling; developing a comprehensive danger warning system based on the obtained results and testing its functionality. The following **methods** were applied in this study: a process-based approach to investigate the mechanisms of road traffic accident occurrence, statistical analysis of hazardous areas and maneuvers, and performance analysis of computer vision models for real-time object detection and tracking and driver notification. Additionally, road situations were simulated and modeled using the BeamNG.tech environment. The **results** include the development of a methodology based on computer vision and mathematical models for identifying hazardous situations on the road and the creation of an approach for prompt notification of road users using cloud technologies, IoT devices, and the GeoHash algorithm. An information system that allows drivers to receive warnings about potential hazards along their route has been proposed. **Conclusions**: this study confirms the successful development of a software system for forecasting and notifying drivers about the risk of road traffic accidents. The conducted studies have demonstrated the effectiveness of the proposed algorithm for detecting hazardous situations and technological solutions for road infrastructure integration. Experiments conducted using BeamNG.tech have confirmed the functionality of the developed system, which can be applied to minimize the risk of road traffic accidents in designated hazardous areas.*

Keywords: *Information Technologies Development; Intelligent software system; model for vehicles crash prediction; Machine Learning; Computer Vision; Nvidia Jetson; Messages routing optimization; GeoHash; Internet of Things.*

1. Introduction

1.1. Motivation

The growing urbanization of modern cities is accompanied by the intensive use of motor vehicles, an integral part of modern life. However, the increase in the number of cars and their speed leads to an increase in the frequency of road traffic accidents (RTAs), which is confirmed by statistical studies [1, 2]. Particular attention should be paid to the problem of pedestrian collisions, as their share in the overall structure of road traffic accidents shows an upward trend [3]. Despite significant progress in the implementation of active safety systems, comprehensive road safety remains a relevant problem. The automotive industry offers a wide range of technological solutions to minimize the risk of accidents, including adaptive cruise control, lane-keeping assistance, pedestrian detection, anti-lock braking system (ABS), blind spot monitoring, etc. However, all these systems are primarily focused on the safety of a particular vehicle and do not consider dangers outside the range of their sensors. Most active automotive safety systems are based on radar and video analysis technologies. For example, the BMW KAFAS system [4] recognizes road signs and displays them on the dashboard, as well as provides pedestrian identification and automatic emergency braking in the absence of a driver’s reaction (up to 50 km/h).

Other technological solutions include the automatic high-beam switching system [5], which detects oncoming traffic and adjusts the lighting intensity. However, the effectiveness of this function depends on the cleanliness of the optical elements of the camera, which can lead to malfunctions. Another innovative solution is automatic parking, which uses ultrasonic sensors and allows the vehicle to perform maneuvers independently without direct driver intervention.

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The night vision system, which operates based on thermal imaging cameras, has received special attention [6]. In BMW, this system recognizes objects (i.e., pedestrians and animals) in the dark and illuminates them with fog lights to improve visibility. This significantly increases the driver's awareness of possible roadway threats.

Despite the diversity of modern automotive technologies, they mostly perform auxiliary functions. Systems such as ABS, brake force distribution, traction control, and electronic differential lock remain fundamental elements of active safety. Their main purpose is to maintain vehicle stability in emergency situations, for example, when a pedestrian unexpectedly appears on the road or other road users violate the rules.

Notably, none of the modern safety systems is an absolute guarantee of avoiding accidents, as the final decision and speed of response remain with the driver. In stressful or unexpected situations, a person may not have time to properly assess the danger, which reduces the effectiveness of even the most advanced technologies.

Thus, an intelligent hazard warning system capable of operating outside the range of standard car sensors must be developed. A separate problem or disadvantage is the availability of technology: most modern systems are integrated exclusively into new car models, which disadvantages owners of vehicles without such equipment. Therefore, a promising direction is to create a universal solution that can function regardless of the design features of the car and ensure that the driver is effectively informed of potential threats.

1.2. State of the Art

Among modern approaches to traffic accident forecasting, regression analysis methods that allow identifying key factors that affect the likelihood of an accident are receiving considerable attention. The use of such methods enables the formation of dynamic risk statuses that can be updated in real time. In particular, one of the possible scenarios for applying this approach involves displaying the probability of getting into an accident directly on the dashboard of a car when starting to drive. Based on the statistics of the Ministry of Transport of New Zealand [7], such a system can assess the level of risk in a particular place under certain road and weather conditions and predict the possible level of damage in the event of an accident. The result of this study is the creation of mathematical models that allow the assessment of the potential consequences of an accident depending on various factors. The analysis of statistical data shows that the presence of drugs in the driver's blood is the most significant factor affecting the likelihood of an accident. This factor significantly increases the risk of an accident because it affects the speed of reaction, coordination, and decision-making adequacy.

In Fig. 1 shows the list of factors considered and their impact on the regression model.

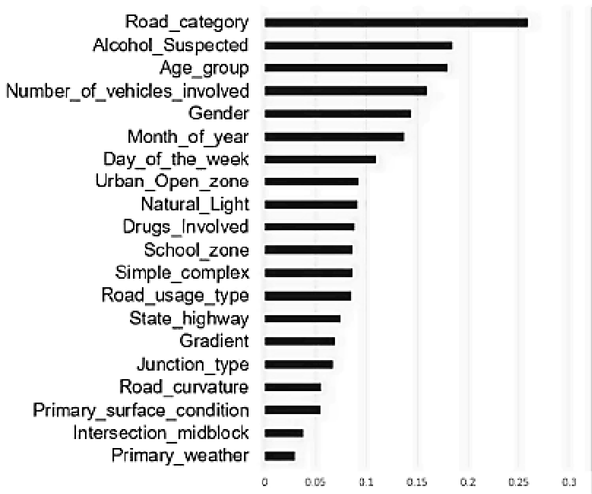

Fig. 1. The factors impact on the regression model [7]

The next research [8] focuses on the integration of advanced algorithms and machine learning techniques to improve traffic management and emergency response systems. For instance, Berhanu et al. emphasize the use of adaptive routing algorithms, such as NSGA-II and MOPSO, which can optimize emergency response planning and traffic flow control, thereby mitigating congestion and reducing the likelihood of accidents in both low- and high-income countries.

The next research [9] investigated connected and autonomous vehicles (CAVs) as a transformative approach to accident prevention. According to Ahmed et al., the implementation of automated driving functions could significantly reduce human error, which is responsible for over 90% of crashes, potentially saving thousands of lives annually.

The implementation of Artificial Intelligence technologies in traffic accident prediction highlights the shift toward smart infrastructure solutions. The following research [10] points out that AI can evaluate real-time risks on roads, enhancing proactive measures to prevent accidents before they occur. This AI integration facilitates a more responsive and data-driven approach to understanding and mitigating traffic incidents. Data-driven methodologies are increasingly required for a detailed understanding of traffic accident patterns. For instance, in the next one research [11] shows the usage of a machine learning framework for accident severity modeling, showcasing the potential of advanced statistical approaches to improve decision-making in traffic safety.

Similarly, the authors of the following work [12] focused on developing sensor systems for wildlife detection, emphasizing the importance of timely interventions to prevent accidents caused by environmental factors.

Using deep learning models to predict traffic accident severity, the next research [13] showcasing the capacity of neural networks to interpret complex data from numerous sources, which improves the interpretability of the models used for such predictions.

Cheng's study [14] on the SARIMA-LSTM model further illustrates how by effectively capturing temporal dependencies in the data, hybrid models can substantially enhance traffic accident forecasting accuracy. The results indicate that the combination of models can yield more reliable predictions, significantly aiding decision-making in road safety interventions.

Gatarić et al. [15] investigated the application of artificial neural networks (ANN) for predicting traffic accidents, emphasizing how non-linear models can integrate various subjective and objective factors contributing to accidents. Their results indicate a promising future for ANN in addressing accident prediction complexity.

In examining factors influencing traffic accident severity, the researchers of this work [16] integrated multiple machine learning models to analyze accident data collected from highway sections, demonstrating how gradient boosting techniques can effectively pinpoint significant risk factors contributing to severe accidents. This multifaceted approach illustrates the value of machine learning in deriving actionable insights for enhancing road safety measures.

1.3. Objectives and the approach

The problem of road accidents remains relevant, and individual car safety technologies are being developed, road infrastructure is being improved, and autopilot systems are being introduced to address it. Statistical analyses are also used to predict accidents under certain conditions.

However, technology that can analyze data from a particular road section in real time and warn drivers of possible emergencies is needed. This approach will significantly reduce the number of accidents because the information will come directly from the traffic area and not be based on historical data. It is important that the proposed system interacts with existing safety technologies, complementing their functionality rather than replacing it.

This study aims to create an intelligent system model for road traffic accident prediction that will notify the driver of potential dangers on the way. To achieve this goal, the following tasks must be performed:

- consider and identify the best computer vision model for classifying and tracking objects on a single-board Nvidia Jetson computer;
- create an optimized solution for receiving a driver's hazard notification;
- create an algorithm for detecting potential hazards using data from the computer vision and mathematical models.

The research includes the following sections:

- Section 1 is devoted to explaining the problem of car accidence, describes the latest views and developments regarding the task of car accidence prediction, and outlines the necessity of creating an intelligent system model for road traffic accident prediction that will notify the driver of potential dangers on the way;
- Section 2 shows the investigation of the causes of road traffic accidents, which points to the reasons and nature of the occurrence of car accidents;
- Section 3.2 includes a review of the computer vision models for the classification of the prerequisites for car crash occurrences on the image. The YOLOv8 and TrafficCamNet_1.3 models are used, and Jetson TX2 is considered the hardware;
- Section 3.3 presents an improved approach for the task of classification of car accidence prerequisites, which uses the computer vision model TrafficCamNet_1.3 for car classification on image and overlapping car trajectory projections to identify possible car accidence;
- Section 4 describes the architecture, UML diagrams for the created software, and error handling;
- Section 5 is related to results explanation of using the software system, which is built on top of the defined model for possible car accidence revealing;
- Section 6 relates to the conclusions drawn during the work on this research.

2. Investigation of road traffic accidents causes

The human factor remains the main factor leading to road accidents. Human behavior determines the course of events on the road, affecting the likelihood of accidents. According to the annual U.S. analytical report The Federal Highway Administration [17] statistics show a gradual decrease in the level of road traffic deaths between 2022 and 2024, indicating a positive trend in road safety (Fig. 2).

Table 1 presents statistics on fatalities depending on the impact direction on passenger crashes.

From the above data, we can conclude that the probability of fatalities decreases with the size of the vehicle. This is because cars with a smaller mass absorb less impact energy, which leads to a much greater load on the human body during a collision.

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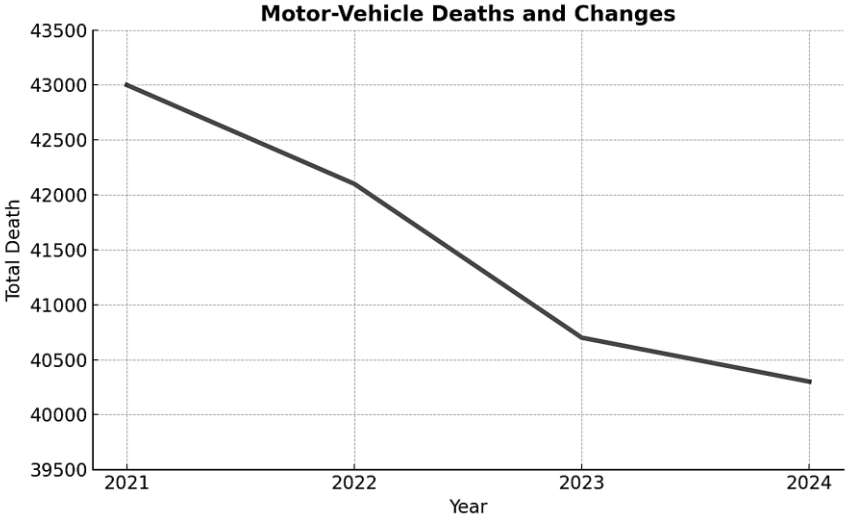

Fig. 2. Vehicle crash death count trend [17]

Table 1

The number of fatalities depends on the direction of impact [17]

Impact direction	Cars	Pickups	Sport Utility Vehicle
Front	8076	2811	4043
Side	3551	811	1271
Rear	744	187	385
Flips	1449	892	1104

According to the US road accident fatalities reports, the most dangerous type of collisions are frontal impacts, followed by side impacts. Based on this, it can be assumed that such accidents most often occur in critical areas of road infrastructure, particularly on intersections where there is a high probability of a side impact, as well as in cases of loss of control, which can lead to a head-on collision.

A systematic review and meta-analysis focused on the prevalence of seat belt use among drivers and passengers, emphasizing its critical role as a cost-effective preventive measure in reducing the severity of injuries, disabilities, and fatalities resulting from road traffic accidents [18]. Their research highlights that a significant proportion of deaths from motor vehicle crashes occur among vehicle occupants, underscoring the need for seat belt usage as a fundamental safety practice. Kargar et al.’s findings are particularly relevant in the context of global road safety initiatives, as they align with the recommendations of the World Health Organization on enhancing seat belt compliance to mitigate road traffic injuries. Despite the known benefits of seat belt use, compliance rates remain suboptimal in many regions, necessitating targeted interventions to promote their usage. This research contributes to the broader discourse on traffic safety by providing empirical evidence that supports policy-making and public health strategies aimed at increasing the adoption of seat belts.

Moreover, recent studies have highlighted the role of specific conditions, such as weather and road surface conditions, in intensifying the severity of accidents. For instance, research [19] explored the impact of rainstorm conditions on traffic accidents, revealing that climatic factors, alongside road conditions, play a crucial role in determining accident severity. This aligns with the findings of other studies that emphasize the need for comprehensive data collection and analysis to accurately predict accident outcomes [20-21].

The next research, which is based on statistical data [22], identifies the most dangerous maneuvers, including the following:

- Continuing to drive without changing direction after hazard detection. This maneuver is responsible for 62% of all fatal accidents in the United States.
- Driving on serpentines, sharp turns, and mountainous terrain at a speed exceeding the speed limit. This type of maneuver accounts for 20.63% of fatal accidents in the United States. The main reason is that drivers overestimate their own driving skills and vehicle capabilities. The high proportion of accidents is also explained by the terrain: approximately 50% of the US territory is covered by mountain ranges, whereas 95% of the territory in Ukraine is flat, which significantly reduces the prevalence of this risk.
- Turning left. This maneuver causes 7% of all fatal accidents in the United States, but it is often considered one of the most dangerous maneuvers in Ukraine, along with overtaking. The main risk of a left turn is that the vehicle crosses into the oncoming lane, where there may be other cars. The danger of this maneuver increases especially in limited visibility when the oncoming traffic has two or more lanes, which makes it difficult to assess the road situation. An additional risk factor when making a left turn is the driver’s excessive cognitive load. While performing the maneu-

ver, he or she must simultaneously control vehicles in the oncoming traffic, monitor for possible pedestrians, and assess other potential obstacles;

− Overtaking a motor vehicle. This maneuver is characterized by an increased level of risk, as it combines high speed and oncoming traffic. Incorrect overtaking can lead to a head-on collision or loss of vehicle control.

The latest EU road accident fatalities report [23] displays the decreasing trend of fatality occurrences (Fig. 3).

The data presented in this analysis were obtained from the CARE (Community Database on Accidents on the Roads in Europe), which compiles detailed records of individual road accidents resulting in death or injury based on reports collected by national authorities from police and hospital sources across European countries.

The number of road traffic fatalities in EU countries has declined significantly over the past decade, with a 16% reduction observed between 2013 and 2023. This downward trend was largely consistent, except in 2015, 2021, and 2022, when modest increases of 0.9%, 5.7%, and 3.7%, respectively, were recorded relative to the previous year.

The marked decrease in fatalities in 2020 (−17.3% compared with that in 2019) is likely attributable to the COVID-19 pandemic, during which widespread lockdowns and mobility restrictions significantly reduced traffic volumes across Europe.

The Fig.4 illustrates the number of road traffic fatalities per million inhabitants across countries in 2023.

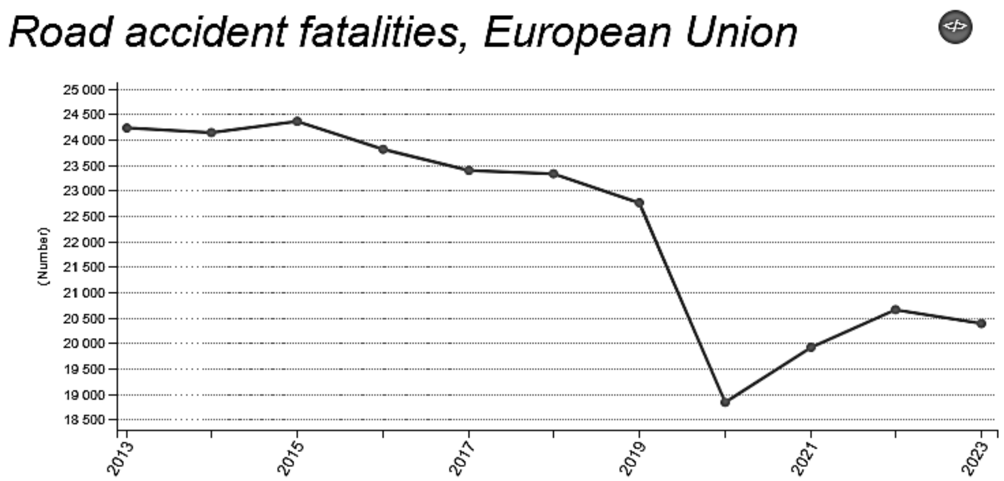

Fig. 3. A recent EuroStat report of road accident fatalities [23]

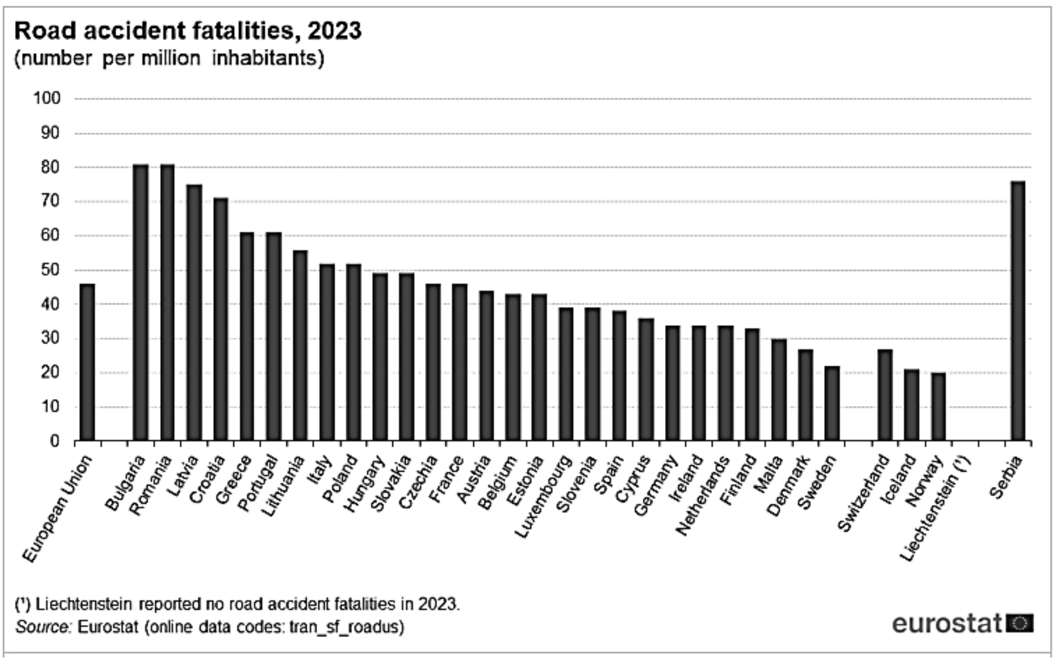

Fig.4. Road accident fatalities [23]

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3. Materials and methods of research

3.1. Methods overview

This paper considers approaches for classifying a road situation in terms of whether it is dangerous or not. For this purpose, we deployed the computer vision algorithms TrafficCamNet_1.3 [24] and YOLOv8 [25] on a single-board computer Jetson TX2. The MQTT message broker of AWS IoT Core was used to send notifications to the user. The BeamNG.tech software [26] was used to create typical traffic scenarios. To use the YOLOv8 model, a dataset that described a dangerous left turn situation was created.

The TrafficCamNet_1.3 model was used as a pre-trained model for car detection tasks. The TrafficCamNet 1.3 model, developed using NVIDIA's TAO Toolkit, is an object detection model based on the DetectNet_v2 architecture with a ResNet-18 backbone. It is designed to identify four object classes: cars, persons, road signs, and two-wheelers. The model was trained on a proprietary dataset containing more than 200,000 images, including approximately 160,000 traffic camera images and 40,000 dashcam images, yielding more than 3 million labeled instances primarily focused on vehicles. The exact training parameters are not publicly disclosed.

The following training parameters were used for training the YOLOv8 model:

- Image size: 640x640 pixels
- batch size: 16
- number of epochs: 100
- learning rate: 0.01
- optimizer: Stochastic Gradient Descent

3.2. Classification of road traffic accidents causes on an image

The first approach for identifying hazardous situations was to use the YOLOv8 model trained on the basis of a dataset with images describing a particular hazardous situation [27]. For example, a left turn across oncoming lanes was considered (Fig. 5).

The dataset comprises two image categories: danger (illustrating hazardous scenarios) and non-danger. The model is intentionally kept straightforward and focuses on a specific dangerous situation: making a left turn across oncoming traffic. This scenario arises when one lane remains unoccupied while the adjacent lanes have stationary vehicles yielding to a driver attempting to turn left. In such cases, some drivers acknowledge the left-turning vehicle, but a driver traveling in the empty lane may not realize why the other lanes are at a standstill. If a left-turning driver proceeds across, they may unexpectedly enter the path of the oncoming vehicle in the open lane, increasing the risk of an accident [27]. The pictures which were used there were 640x640 px resolution and represent danger and non-danger cases. The ratio between classes was 1:1. That is, 150 pictures were created for one class and 150 for another.

Fig. 5. Example of turning left across oncoming lanes case [27]

The general approach for image classification into danger and not—danger classes can be considered as follows: if cars' trajectories are intersected or can be intersected in a short period of time and these cars' drivers cannot see each other in line of sight, then this case can be considered as danger. The opposite way for classification of non-danger cases: If cars' drivers are able to see each other in direct sight during maneuvers, then these cases are classified as non-danger. A left turn across an oncoming lane is one of the dangers.

The YOLOv8 model validation included the usage of the following metrics: Mean average Precision with IoU, Time to train, occupied GPU memory, model size, Loss CLS, Loss box, inference time, Recall, Precision. The following formulas describe these metrics.

The Precision metric has the following formula:

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}, \tag{1}$$

where TP (True Positive) – the number of correctly predicted positive cases;

FP (False Positive) – the number of cases where the model incorrectly predicted a positive result.

The Recall formula is as follows:

$$\mathrm{Recall} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FN})}, \tag{2}$$

where TP – the number of correctly predicted positive cases;

FN – the number of cases where the model predicted negative results but were actually positive.

The IoU formula is as follows:

$$J(A,B)=\frac{|A\cap B|}{|A\cup B|}, \tag{3}$$

where A,B – areas, and intersection is the area where the predicted bounding box overlaps with the ground truth bounding box;

Union – the total area covered by both the predicted and ground truth bounding boxes, excluding the overlapping area.

The Loss Box formula is as follows:

$$L_{box}(t^u, v)=\sum_{i\in\{x,y,w,h\}} L_1^{smooth}(t_i^u - v_i), \tag{4}$$

where there is a sum of $L_1^{smooth}(t_i^u - v_i)$ – which denotes Smooth L1 between the compared predicted box and the ground-of-truth box;

t_i^u – predicted box;

v_i – ground of truth for the box;

$i\in\{x,y,w,h\}$ – iteration over the four box components: x, y, width, and height.

The Cross Entropy Loss CLS formula is the following:

$$L_{cls}(p,y)=-[y\log(p)+(1-y)\log(1-p)], \tag{5}$$

where y – actual label,

p – predicted probability of the instance being in a class.

The Fig. 6 displays Recall metrics during model training. X-axis displays epochs and Y-axis recall metric.

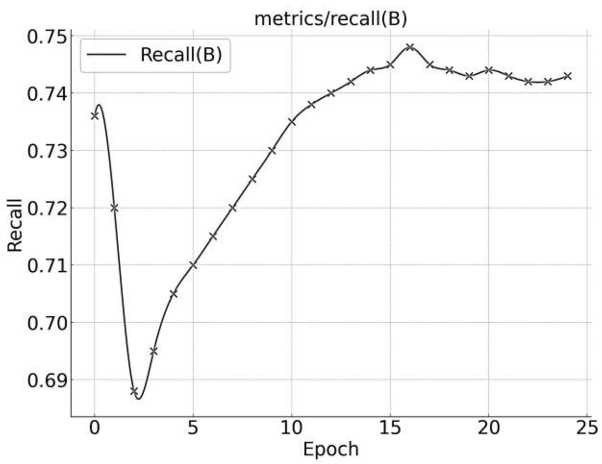

Fig. 6. Recall chart

The Fig. 7 displays the Loss box metrics during model training. The x-axis denotes the epochs, and the y-axis denotes the loss value. The training box loss is steadily decreasing, suggesting that the model is improving its ability to localize objects. It starts around 0.07 and ends just below 0.045, which is a significant reduction.

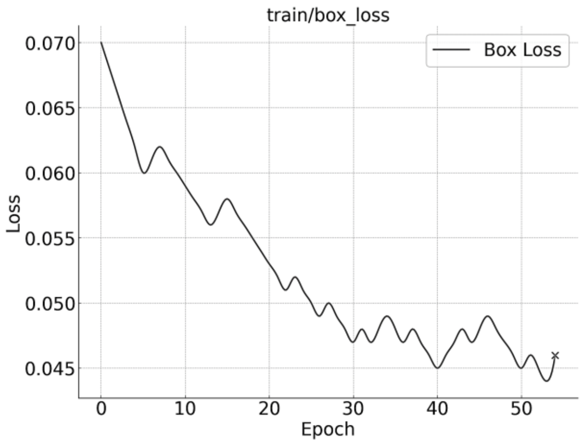

Fig. 7. Loss Box chart

The Fig. 8 represents chart of Cross Entropy Classification Loss metric, which was obtained during model training. The x-axis displays the epoch count, and the y-axis shows the loss value.

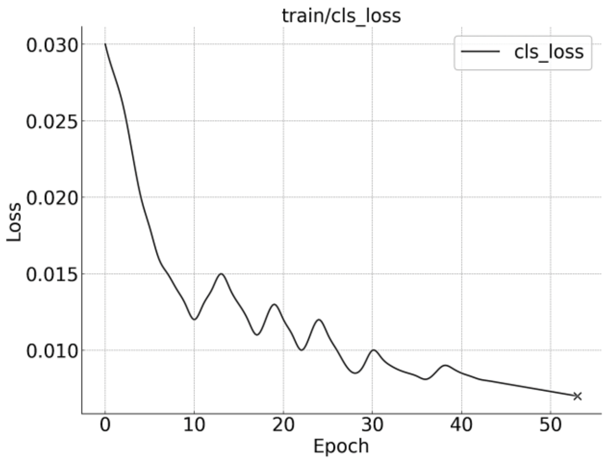

Fig. 8. Loss CLS chart

The Mean Average Precision formula is as follows:

$$mAP=\frac{1}{N}\sum_{i=1}^{N} AP_i, \tag{6}$$

where N – number of classes;

AP_i – average precision for a given class.

At the initial epoch, the classification loss was approximately 0.030, indicating a relatively high degree of misclassification. The loss exhibits a monotonic decreasing trend as training progresses, characterized by a

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sharp decline in the early epochs (0–10), followed by a more gradual reduction with minor oscillations. This behavior is typical of well-behaved optimization dynamics, where the model quickly learns coarse patterns initially and then fine-tunes its predictions in later epochs.

he Fig. 9 displays the mean average precision metric collected during model training. The x-axis displays the epoch count, and the y-axis shows the mean precision value.

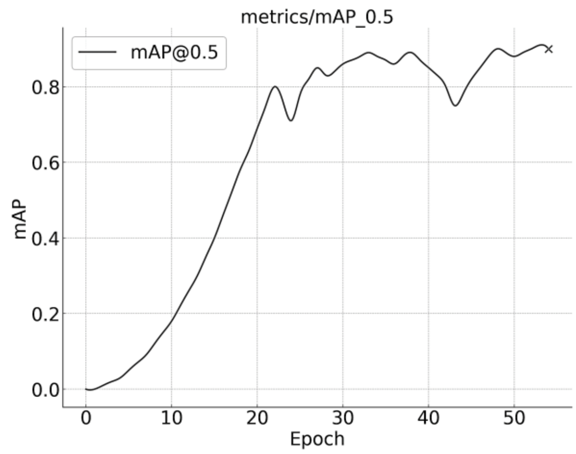

Fig. 9. mAP metric chart

All metrics experienced a sharp decline at the 40th epoch. This can be attributed to the model overfitting to the training data at this stage, leading to reduced generalization during validation. As a result, the model struggles to effectively distinguish classes, which not only lowers the overall accuracy but also gives a misleading impression of fewer errors.

Table 2 shows the results obtained during the model evaluation:

Table 2

Evaluation results of YOLOv8

Metric Name	16 epochs	54 epochs	80 epochs	100 epochs
Recall	0.726	0.742	0.75	0.738
Precision	0.846	0.845	0.834	0.821
mAP50	0.83	0.84	0.84	0.829
mAP95	0.609	0.621	0.622	0.614

After 54 epochs, the model was selected for deployment on the Nvidia Jetson TX2.

However, the proposed method of road accident prediction is difficult to implement due to several design limitations.

– the main problem is the large amount of training data required to classify dangerous situations accurately. For example, to identify only one maneuver – turning left – the model must consider a wide range of variations: different background environments, vehicle types, their positions on the road, and differences between safe and dangerous scenarios. Furthermore, a left turn is only one of many risky maneuvers, and the number of possible scenarios for its execution is virtually unlimited. This creates the problem of over-expanding the dataset, which complicates the model training and increases computational costs. The idea was to optimize the approach by reducing the uninformative context:

– reduction of background information (city, mountains, forest, highway), as it does not affect the maneuver mechanism;

– vehicle type because the nature of the maneuver does not depend on whether it is performed by a car, truck, or bicycle.

Moreover, as an enhancement, characteristics, such as road markings, can be added to help better classify the image, which may be invisible or absent. However, this enhancement is highly costly to prepare because the image annotation process is performed manually. Only a human can correctly determine which lines and objects should be highlighted and which are irrelevant. In addition, this method does not solve the problem of variability in the requirements of road accidents, as their occurrence scenarios are too diverse. Fig. 10 shows a possible enhancement method.

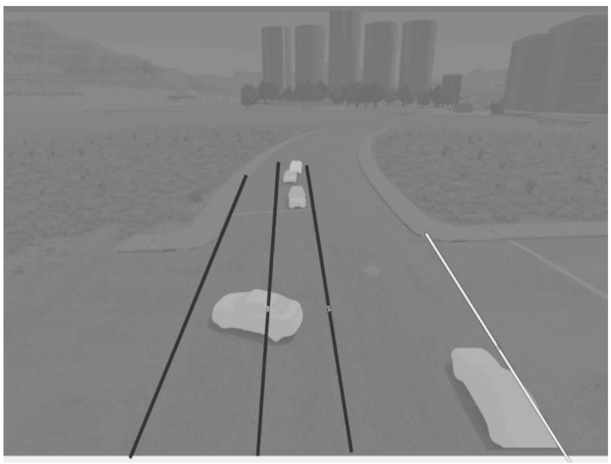

Fig. 10. Elimination of unnecessary case context

Thus, the proposed approach cannot be argued to significantly improve the accuracy of detecting dangerous situations.

3.3. Enhanced model for classification of possible car accidence using computer vision and math model

Based on this, new requirements for an intelligent system model for road traffic accident prediction arise, which should ensure the system's efficiency and practicality:

– minimize the size of the training dataset to reduce resource requirements;

– simplified preparation of training data that does not require significant human intervention;

– high speed and accuracy of image object classification;

– the ability to deploy the model on single-board computers ensures the mobility and accessibility of the solution.

It was decided that it was necessary to use a general classification model that could detect a car and then predict whether the cars would likely crash using a certain model. This model, which determines whether the cars are likely to crash, uses a projection of the direction of the car's movement. If the projections of the cars' movement intersect, then an accident is possible (Fig. 11).

Fig. 11. The methodology of definition of the possible crash

4. Software Implementation

The MQTT message broker was used to send/receive notifications, and the Raspberry PI is used for IoT devices that receive notifications and are installed in a car (or it can be a smartphone). The reason for keeping both devices for notification receiving is as follows:

– Modern smartphones can request the current location with a speed of up to 1 Hz, which may be insufficient for some cases. The Raspberry Pi usage allows assembling the high-frequency system for location request; thus, the speed for the location request process can be increased up to 10-20 Hz.

The general approach for receiving notifications is to receive it from the AWS cloud message broker, analyze it, and determine whether the user is within the area where the notification should be displayed. The system activates an audible signal if the car is within the danger zone, warning the driver of a potential threat.

This approach ensures confidentiality, as information about the driver's location remains locally in the car's device without transferring personal data to third-party services and over the network. To optimize the flow of incoming messages to the IoT device in the car, the GeoHash [28] algorithm should be used. This approach divides the world map into fixed geographical sectors of a certain size, greatly simplifying the process of routing messages.

Each GeoHash quad corresponds to a separate topic in the MQTT broker to which IoT devices installed in vehicles will subscribe. This structure minimizes the number of unnecessary messages because the device receives only data relevant to its current geographic location.

The flow diagram for the message receiving process is shown in Fig. 12.

This flow chart describes the mechanism of how a message about a certain warning is received. There are a few components: a car, IoT device (or smartphone) installed in a car, AWS IoT Core, and AWS RDS. The process starts when the engine is started. This invokes checks for subscription presence. Once a positive response from the backend about the subscription status is received, the IoT attempts to obtain the current location, calculate the geohash, and subscribe to a particular topic using the geohash. Once the message from the topic is received, the IoT checks whether the car is within a defined polygon, based on the message. This polygon is a place on a crossroad, which the cameras' installers marked as a zone-of-action, indicating that cars in this polygon should receive messages if any warnings are found.

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The next diagram (Fig. 13) explains the publishing flow of the message about the found potential car accidence.

This diagram shows the mechanism of sending a message about possible car accidence to the MQTT message broker. There are few components in general: Nvidia Jetson, AWS Cloud. Initially, during the camera-device (Nvidia Jetson) setup process, installers provide the software with static input information based on which camera-device subscribes to the particular topic on AWS IoT MQTT broker. Then, Jetson processes the image and classifies the vehicles, calculates the possible cars' trajectory intersection, and sends warning

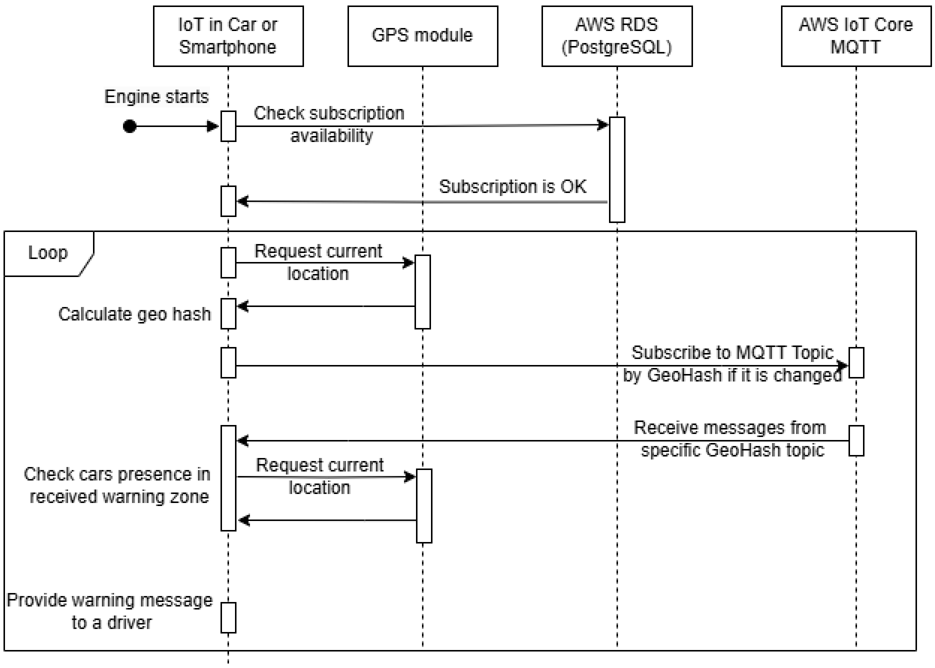

Fig. 12. Flow chart for the message receiving process

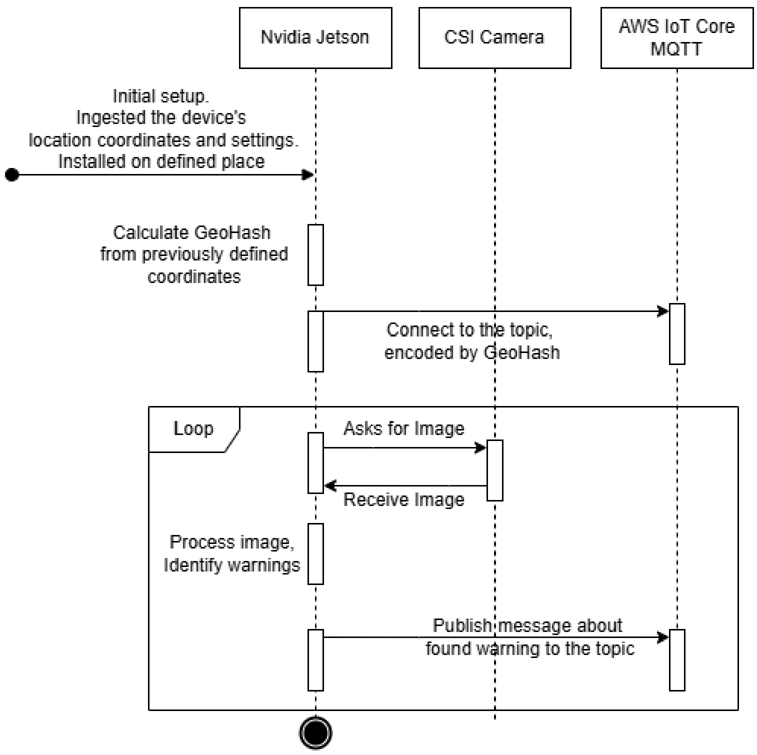

Fig. 13. Flow chart for the message publishing process

messages with defined metadata in case any violation is found.

4.1. Error Handling

The real-time intelligent notification system's error handling should include handling for false positive classification and cloud disconnecting cases.

In terms of incorrect classification, receiving a warning message is ok when there are no real danger cases found. In cases where a danger situation is present but is not recognized properly, it can be fixed with proper model training and receiving a high average precision metric value during the testing system on each installed danger road part. The system should be tested before it goes live for workability on the particular place of installation. If the system in the test mode shows a low Average Precision metric, the model should be adjusted for the currently installed place.

The cases of cloud disconnections should be handled with alternative Internet connection on the camera edge device side, which allows switching from one way to another, in case of any issues with the primary one way for Internet access. The Exponential backoff algorithm for sending notification into MQTT message broker should be used in the case of unsuccessful message sending.

In terms of disconnection handling from the client side (installed IoT device into a car), the following approaches can be used:

– Usage of QoS (Quality of Service) level 1, which sets the delivery of message at least once.

– Persistent session usage, which allows the retention of the subscription state and undelivered QoS 1 or 2 messages while the client is offline.

– Usage of alternative Internet connection warmed up and ready for replacement in case of any issues with the primary connection.

5. Results and Discussion

According to the results of testing the YOLOv8 model on the Jetson TX2, the performance of the YOLOv8 model on this version of the single-board computer is significantly inferior to that of the TrafficCamNet_1.3 model. Table 3 shows the comparison results in Table 3.

Table 3

Comparison of YOLOv8 and TrafficCamNet_1.3

Metric Name	YOLOv8m	TrafficCamNet_ 1.3
Average on 10 runs - GPU latency, ms	155.703	6.927
Throughput, qps	6.407	140.517
Latency: min, ms	153.808	7.052
Latency: max, ms	157.84	8.735

Various scenarios were designed to test an intelligent system for predicting road traffic accidents. However, current research includes the results from only one case, which tests the system from a performance point of view. The exciting near-house territory or turning left across oncoming lines involves only one vehicle at high speed and another almost stops, which, in general, cannot fully check the system. As an experimental scenario for using an intelligent system model for road traffic accident prediction, a case was designed where a traffic light-controlled intersection exists. The exit from one road is downhill, and there is also a building on the right side of the car moving up. This building prevents the driver of the red car from ensuring that it is safe to enter the intersection (Fig. 14).

The TrafficCamNet_1.3 model was used to detect and classify cars in this case. An example of the work is shown in Fig. 15.

Fig. 14. Case created for the experiment

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The purpose of the experiment was to determine the time when the system notifies the driver of a potential threat, the time when the driver stops completely after receiving a sound signal (on a certain type of car), and the model's limitations for classifying and tracking the car. A laptop was used as an IoT device to run the experiment scenarios created in the BeamNG.tech software. The location of the car was determined based on its position on the simulator map. Table 4 shows the results of the experiment using a 1425 kg sedan car weighing 1425 kg. Conventional disc brakes with 1 piston was there.

The analysis of the results of the first experiment allows us to draw the following conclusions:

– the effectiveness of the system is confirmed at a vehicle speed of no more than 50 km/h for the vehicle type in the experiment;

– the average time of message transmission and processing is 0.3 s, which is fast enough to give the driver additional time to react;

– the braking time varies between 1.7 and 2 s.

However, in 50% of the cases, a collision still occurred. The main reason for this was the late triggering of the system, which was caused by the late detection of the car or its loss during the threat analysis. To fix this problem, the computer vision algorithm must be optimized by training the model on datasets with different input image sizes, which will improve recognition accuracy and system stability.

The next experiment was conducted under an identical scenario but using a different vehicle type. The car weighed 1660 kg, had a wagon body type, and was equipped with a three-piston sports brake system. Table 5 presents the results.

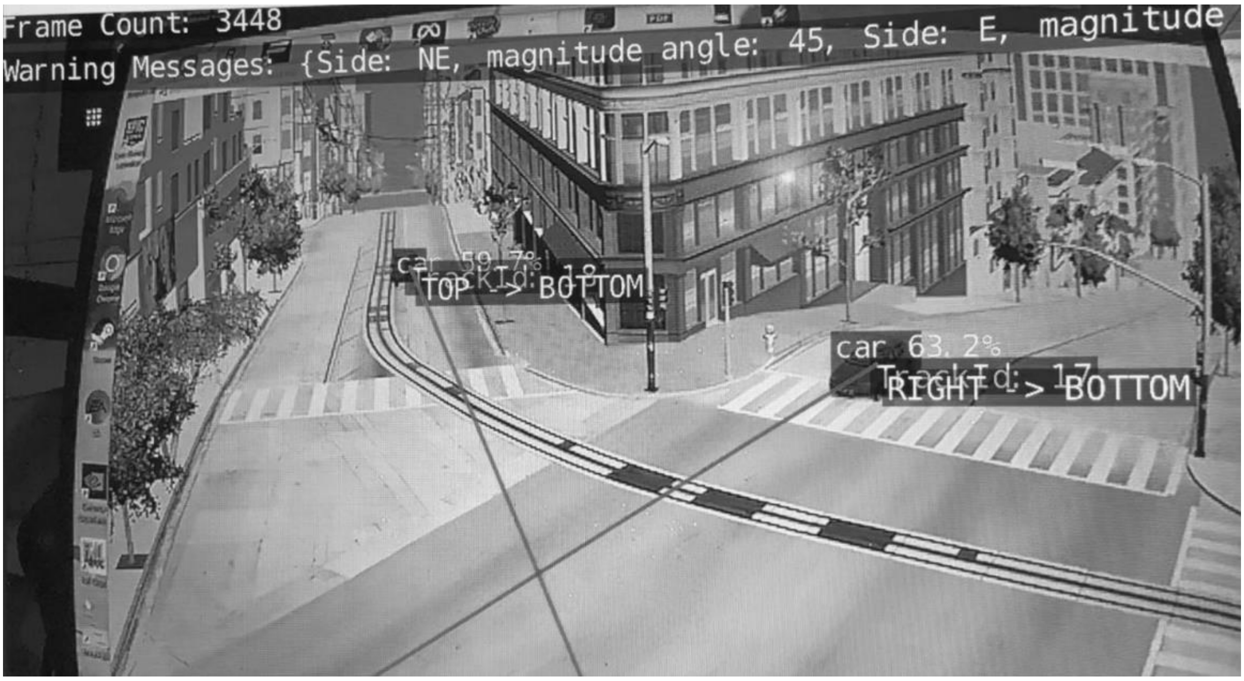

Fig. 15. Example of how the model performs

Table 4

Results of experiments for the created case with a car weight of 1425 kg

The time before notification sent	The time, when IoT received message	The time, when car fully stopped	The speed at the moment of notification received; km/h	Crash happened
2025-01-05T12:40:02.709622	2025-01-05T12:40:02.933484	2025-01-05T12:40:05.114334	42	TRUE
2025-01-05T13:08:56.834051	2025-01-05T13:08:57.076655	2025-01-05T13:08:58.772655	37	FALSE
2025-01-05T13:09:27.781746	2025-01-05T13:09:28.030199	2025-01-05T13:09:29.102009	51.38	FALSE
2025-01-05T13:09:57.748407	2025-01-05T13:09:57.994106	2025-01-05T13:09:59.253262	52.67	TRUE

Table 5

Experimental results for the wagon-type vehicle and 1660 kg weight

The time before notification sent	The time, when IoT received message	The time, when car fully stopped	The speed at the moment of notification received; km/h	Crash happened
2025-01-05T14:16:54.601413	2025-01-05T14:16:54.998645	2025-01-05T14:16:56.905827	50	FALSE
2025-01-05T14:17:09.322504	2025-01-05T14:17:09.649457	2025-01-05T14:17:12.297685	66.06	TRUE
2025-01-05T14:17:55.841201	2025-01-05T14:17:56.151540	2025-01-05T14:17:57.848792	61	TRUE
2025-01-05T14:18:40.917595	2025-01-05T14:18:41.222709	2025-01-05T14:18:42.918078	77	TRUE
2025-01-05T14:18:58.137268	2025-01-05T14:18:58.457782	2025-01-05T14:18:59.872115	41.6	FALSE
2025-01-05T14:19:10.642923	2025-01-05T14:19:10.975277	2025-01-05T14:19:12.424491	43.7	FALSE
2025-01-05T14:19:24.891371	2025-01-05T14:19:25.217969	2025-01-05T14:19:26.146659	32	FALSE

This experiment clearly shows the relationship between vehicle speed and accident probability:

- no emergencies occur at speeds of up to 60 km/h, and the system manages to warn the driver in time of an approaching threat from the right;
- the time to send and receive a message remains unchanged at 0.3 s;
- the time for a complete stop of the car ranges from 1.5 to 2.3 s, which corresponds to the previous test results.

However, even with a highly effective braking system, it is impossible to safely avoid an accident when the city's speed exceeds the allowed limit. This confirms the critical importance of speed limit compliance for the effective functioning of the accident prevention system.

6. Conclusions

In this study, we developed and tested an intelligent system model for road traffic accident prediction based on real-time video processing and notification sending. The articles considered for improving road safety mostly use historical data to define patterns and dependencies in data, whereas this research focuses on revealing potential threats in real-time based on information collected from a particular place.

The main practical results are as follows:

- An analysis of the current approaches to road safety was conducted;
- We investigated and tested computer vision models for real-time vehicle detection on the Nvidia Jetson platform;
- A new intelligent system is proposed for detecting dangerous situations, such as vehicle collisions, in real time;
- A system is implemented for routing messages from video stream analysis devices to cars using GeoHash;
- A software architecture that provides high performance, reliability, and scalability through AWS cloud services was developed;
- A prototype of the device for installation on dangerous road sections based on Jetson Orin Nano and IMX219-160 camera was created;
- The system was experimentally tested in different vehicle traffic scenarios using BeamNG.tech [26].

Thus, the proposed model can reduce the risk of accidents in certain dangerous areas, and its effectiveness is confirmed by the test results. The future work that needs to be done is: improvement of computer vision models in the angle of faster car classification and avoiding of classified object tracking loss.

Contributions of authors: conceptualization, methodology**;** formulation of tasks, analysis**;** development of model, software, verification; writing, original draft preparation **– Oleksandr Byzkrovnyi**; analysis of results, visualization; writing – review and editing **– Kirill Smelyakov**; analysis of implementation results, models improvement – **Anastasiya Chupryna**.

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Conflict of Interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, author ship or otherwise, that could affect the research and its results presented in this paper.

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This study was conducted without financial support.

Data Availability

The manuscript contains no associated data.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence methods while creating the presented work.

All the authors have read and agreed to the published version of this manuscript.

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МОДЕЛЬ ІНТЕЛЕКТУАЛЬНОЇ СИСТЕМИ ПРОГНОЗУВАННЯ ДОРОЖНЬО-ТРАНСПОРТНИХ ПРИГОД

О. М. Бизкровний, К. С. Смеляков, А.С. Чуприна

Предмет дослідження полягає у визначенні передумов виникнення дорожньо-транспортних пригод, аналізі найнебезпечніших маневрів механічних транспортних засобів, що можуть спричинити аварійні ситуації, найефективнішого способу оперативного сповіщення водія про потенційну небезпеку. **Мета** дослідження – створення інформаційної системи, що забезпечує своєчасне сповіщення водіїв про можливе виникнення ДТП на визначених небезпечних ділянках руху. **Завдання**: дослідити існуючі моделі комп'ютерного бачення для задачі класифікації і трекінгу об'єктів та визначити найбільш відповідні для використання на одноплатному комп'ютері Nvidia Jetson, дослідити їх продуктивність і технічні обмеження; розробити оптимізоване рішення для оперативного сповіщення водіїв про небезпеку; створити алгоритм виявлення можливих зіткнень автомобілів, що поєднує методи комп'ютерного бачення та математичного моделювання; розробити комплексну систему попередження про небезпеку на основі отриманих результатів та протестувати її працездатність. У роботі застосовано різні **методи**, процесний підхід для дослідження механізмів виникнення ДТП, статистичний аналіз небезпечних ділянок та маневрів, а також аналіз швидкодії моделей комп'ютерного зору для оперативного розпізнавання об'єктів та інформування водія. Додатково використано методи моделювання та симуляції дорожніх ситуацій у середовищі BeamNG.tech. Основні **результати** включають розробку методики визначення небезпечних ситуацій на дорозі на основі комп'ютерного бачен-

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ня та математичних моделей, створення підходу для оперативного сповіщення учасників руху через хмарні технології, IoT-пристрої та алгоритм GeoHash. Запропоновано інформаційну систему, що дозволяє водіям отримувати попередження про потенційну небезпеку на маршруті. **Висновки.** Було розроблено програмну систему прогнозування та сповіщення водіїв про ризик виникнення ДТП на дорозі. Проведені дослідження показали ефективність запропонованого алгоритму визначення аварійних ситуацій та технологічних рішень для інтеграції у дорожню інфраструктуру. Виконані експерименти з використанням BeamNG.tech продемонстрували працездатність розробленої системи, що може бути застосована для мінімізації ризиків ДТП у визначених небезпечних зонах.

Ключові слова: розробка інформаційної технології; інтелектуальна програмна система; модель прогнозування дорожньо-транспортних пригод; машинне навчання; комп'ютерне бачення; Nvidia Jetson; оптимізація маршрутизації повідомлень; GeoHash; Internet of Things.

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