Prus Bohdan, PhD Student, Department of Software Engineering, Vinnytsia National Technical University, Vinnytsia, Ukraine, ORCID: https://orcid.org/0009-0008-7214-0949

Rakytyanska Hanna, Candidate of Technical Sciences, Associate Professor of the Department of Software Engineering, Vinnytsia National Technical University, Vinnytsia, Ukraine, ORCID: https://orcid.org/0000-0001-5863-3730

TRANSFER LEARNING SOFTWARE SYSTEM FOR ROAD RISK ASSESSMENT BASED ON OBJECT AND HUMAN BEHAVIOURAL FEATURES

Abstract

This paper introduces a software system designed for transfer learning, specifically for evaluating road risks based on object and human behavioural features under the limited computational resources of edge devices. The relevance of this study stems from the fact that modern road scene analysis systems are primarily focused on object detection and scene understanding, yet they insufficiently account for the behavioural characteristics of traffic participants and the specifics of transferring behavioural risk representations into compact models for online deployment.

The aim of this work is to develop a transfer learning software system for real-time online assessment of road risks based on the integration of object-based and behavioural features. A road scene representation model is proposed, which includes spatial, trajectory, and behavioural characteristics, as well as a mathematical model for risk assessment within the Safe–Suspect–Unsafe classes.

A teacher–student transfer learning model with a behaviour-aware loss function is developed that, unlike traditional knowledge distillation approaches,

preserves risk-oriented behavioural knowledge. A software architecture integrating object detection, feature extraction, behavioural analysis, transfer learning and risk inference for online road risk monitoring is proposed.

Experimental results have shown that behavioural-aware transfer learning improves the accuracy of risk assessment, enhances the detection of critical scenarios, and ensures high consistency of predictions after knowledge distillation while maintaining suitability for deployment on resource-constrained platforms.

The proposed contribution consists in the combination of behavioural features, transfer learning, and risk-oriented scene reasoning within a unified software system for road risk assessment. The practical value of the results lies in the possibility of using the proposed approach in intelligent transportation systems and systems for monitoring hazardous road situations.

Keywords: transfer learning; road risk assessment; road scene analysis; behavioural features; knowledge distillation; edge computing; online monitoring.

1. Problem Statement

The development of intelligent transportation systems, autonomous driving, and decision support systems has driven active progress in methods for road scene analysis, critical situation detection, and road risk assessment [1–4]. Modern approaches are based on object detection, semantic segmentation, and scene understanding; however, object detection alone is insufficient for adequate risk assessment, as danger is determined not only by scene composition but also by spatial interactions, trajectory characteristics, and behavioural intentions of traffic participants [3–6].

Road scenarios become particularly challenging when risk emerges from potentially dangerous behavioural patterns, including conflicting manoeuvres, intentions to cross trajectories, or borderline situations between safe and critical states. Existing risk-oriented approaches are primarily focused either on object-

centric features or on rule-based reasoning, whereas the integrated use of object and human behavioural features within a unified software system remains insufficiently explored [6, 10– 13].

An additional challenge arises when implementing such systems on resource-constrained edge devices, where the use of complex teacher models is limited by inference latency and computational complexity [7–9, 17, 18]. In this context, the use of transfer learning and knowledge distillation to transfer structured risk knowledge into compact student models is promising; however, behavioural-aware knowledge distillation for road risk assessment tasks remains insufficiently explored. This defines the relevance of developing a transfer learning software system for road risk assessment based on object and human behavioural features for online monitoring on resource-constrained devices. In this study, we consider road risk assessment as a joint problem of behavioural scene understanding and transfer learning under edge constraints.

2. Analysis of recent research and publications

2.1. Existing Approaches to Road Scene Analysis and Risk Assessment

Modern approaches to road scene analysis can be conditionally divided into three groups: object-centric methods, behavioural approaches, and scene reasoning models.

The first group includes methods focused on object detection and scene understanding based on deep learning, specifically models of the YOLO family, semantic segmentation, and scene graph approaches [1–4, 16, 17]. Such approaches provide high-quality scene structure representation, but predominantly operate on low-level features and are not sufficiently adapted for direct road risk assessment.

The second group comprises approaches that utilise behavioural characteristics of traffic participants, including trajectory prediction, intention

modelling, and conflict-aware risk assessment [5, 6]. Their advantage lies in considering the potential evolution of hazardous situations; however, such methods often treat behaviour as a separate task rather than as a component of an integrated risk-oriented model.

A promising direction is scene reasoning and three-way decision approaches [10 – 13], which enable transitioning from the traditional model $Risk = f(O)$ to a more general model:

$$Risk = f(O, B) \quad (1)$$

where risk is defined as a function of object and behavioural features. However, a review of the literature shows that software systems which combine these components within a unified software architecture are limited in number.

2.2. Transfer Learning for Road Risk Assessment and Open Challenges

A separate direction of current research is associated with the use of transfer learning and knowledge distillation to transfer knowledge into compact models suitable for deployment on resource-constrained devices [7–10, 17, 18].

Current teacher–student approaches are primarily focused on transferring feature-level knowledge and preserving detection or segmentation accuracy, but insufficiently explore the transfer of risk-sensitive behavioural knowledge in road risk assessment tasks.

Despite significant advances in transfer learning and knowledge distillation approaches, most existing studies are oriented toward detection, classification, or semantic segmentation tasks, whereas the transfer of risk-sensitive behavioural knowledge in road risk assessment remains insufficiently explored. Of particular interest are prototype-guided and granular knowledge-based approaches [9–13], which create preconditions for combining transfer learning with risk-oriented reasoning and interpretable decision-making. However, in the known literature, issues related to the integration of behavioural features into teacher–student

architectures, preservation of knowledge consistency after distillation, and the construction of software systems for online road risk monitoring suitable for edge deployment remain insufficiently addressed.

Unsolved problems remain regarding the integration of object and behavioural features within a unified risk model, the transfer of behavioural risk knowledge in teacher–student architectures, and the construction of software systems for online road risk monitoring on resource-constrained devices.

These limitations define the scientific problem addressed in this work and determine the feasibility of developing a transfer learning software system for road risk assessment based on object and human behavioural features.

3. Purpose of the article

The purpose of the article is to develop a transfer learning software system for online road risk assessment based on object and human behavioural features for resource-constrained edge devices.

To achieve this purpose, the following tasks are addressed:

1. To develop a risk assessment model that integrates object-based and behavioural features for road scene analysis.

2. To propose a teacher–student transfer learning software architecture for preserving risk-oriented knowledge in compact models.

3. To validate the proposed approach experimentally in terms of risk prediction accuracy and online deployment efficiency.

4. Presentation of the main material of the study

4.1. Road Scene Representation Model

Let the input road scene be given by an image I*I*, after processing of which a set of detected objects is formed:

$$G = \{g_1, g_2, \dots, g_n\} \quad (2)$$

Each object is described by a feature vector:

$$x_i = (v_i, d_i, t_i, b_i) \quad (3)$$

where v_i – detection confidence, d_i – estimated distance to the ego-vehicle, t_i – trajectory deviation characteristic, b_i – behavioural features.

Behavioural characteristics are defined as:

$$b_i = (m_i, c_i, s_i) \quad (4)$$

where m_i – motion tendency, c_i – trajectory conflict, s_i – speed behaviour.

The behavioural characteristics are computed from consecutive video frames as follows:

– motion tendency $m_i \in [0,1]$ is defined as the normalized angle of motion relative to the ego-vehicle heading

$$m_i = \frac{|\Theta_i|}{\pi} * \frac{v_i}{v_{max}} \quad (5)$$

where Θ_i is the angle between the object's velocity vector and the forward direction of the ego-vehicle, v_i is the object's speed (pixels/frame), and $v_{max} = 15$ pixels/frame corresponds to the maximum observed speed.

– trajectory conflict $c_i \in \{0,1\}$indicates whether the object's predicted path intersects with the ego-vehicle's path within a critical time window:

$$c_i = 1 \; if \; Time - to - Collision \; (TTC) < 2 \; sec, otherwise \; c_i = 0 \quad (6)$$

where $TTC = \frac{d_i}{v_{rel}}$ with d_i – Euclidean distance to ego-vehicle, v_{rel} – relative approach speed.

– speed behaviour $s_i \in [0,1]$ captures whether the object's speed is appropriate for the road context:

$$s_i = \min(1, \frac{v_i}{v_{limit}}) \quad (7)$$

where $v_{limit}$is the estimated speed limit in the lane region (default $v_{limit} = 10$ pixels/frame for urban scenes).

Thus, the road scene is represented by the structure:

$$S = \{G, X, B\} \quad (8)$$

which combines object and behavioural features.

4.2. Road Risk Assessment Model

Risk assessment is performed within a three-level decision scheme:

$$D = \{Safe, Suspect, Unsafe\} \quad (9)$$

and is defined by the mapping:

$$y = F(I, S) \quad (10)$$

To integrate spatial and behavioural characteristics, an integral risk indicator is introduced:

$$R = w_1 R_0 + w_2 R_b \quad (11)$$

where $w_1 + w_2 = 1$, and R_0 and R_b characterize the object-based and behavioural components of risk, respectively.

The risk class is determined by the rule:

$$y = \arg \max_j \mu_j(R) \quad (12)$$

where μ_j –are membership functions for the risk classes.

The proposed model implements the transition:

$$Risk = f(O) \rightarrow Risk = f(O, B) \quad (13)$$

which better accounts for the behavioural nature of hazardous road scenarios.

4.3. Transfer Learning for Risk Assessment

For knowledge transfer, a teacher–student architecture is used $T \rightarrow S$ where the teacher model transfers structured knowledge representations to a compact student model [7, 9, 14].

Training is performed by minimising the loss functional:

$$L = \alpha L_{det} + \beta L_{feat} + \gamma L_{beh} + \delta L_{risk} \quad (14)$$

where αL_{det} – detection loss, βL_{feat} – feature distillation loss, γL_{beh} – behavioural knowledge loss, δL_{risk} – risk consistency loss.

In contrast to classical knowledge distillation models [7-9, 14, 16], the introduction of the L_{beh} component ensures the preservation of behaviour-aware knowledge during model compression.

4.4. Software System Architecture

The proposed method is implemented as a software system:

$$S = M_d \circ M_f \circ M_b \circ M_t \circ M_r \quad (15)$$

where M_d – object detection, M_f – feature extraction, M_b – behavioural features analysis, M_t – transfer learning, M_r – risk inference.

The functional interaction of these modules forms a sequential processing pipeline of the road scene – from object detection and behavioural feature extraction to knowledge transfer and risk level assessment.

The architecture of the proposed software system and the information flows between its main modules are shown in Fig. 1.

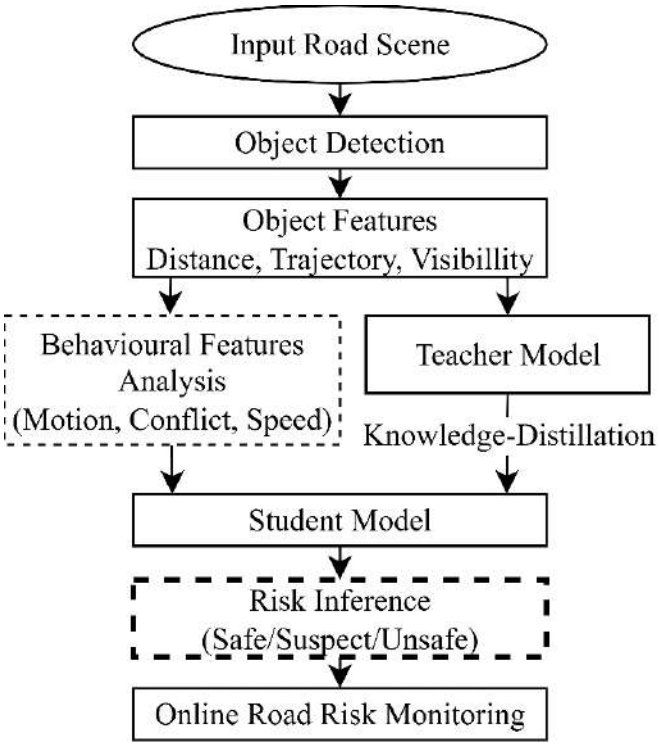


Figure 1. Architecture of the proposed transfer learning software system for online road risk assessment

As shown in Fig. 1, the proposed architecture combines modules for object and behavioural feature analysis with teacher–student knowledge distillation and a risk inference module, enabling online road risk monitoring on resource-constrained edge devices.

4.5. Risk Assessment Algorithm

Risk assessment is performed sequentially through object detection, behavioural feature extraction, knowledge transfer, integral risk calculation, and scene classification.

The algorithm is described by the composition:

$$A = A_1 \circ A_2 \circ A_3 \circ A_5 \circ A_5 \quad (16)$$

and has linear complexity with respect to the number of scene objects, ensuring suitability for real-time operation.

5. Experimental Results and Discussion

The aim of the experimental study is to evaluate the effectiveness of the proposed transfer learning software system for road risk assessment according to the criteria of risk prediction accuracy, speed, and knowledge transfer stability.

For experimental validation, road scenes from open datasets Cityscapes [19] and BDD100K [20] were used, containing scenarios of varying risk levels.

Assessment was performed for three risk classes:

$$D = \{Safe, Suspect, Unsafe\} \quad (17)$$

according to the proposed model.

For comparison, three variants were considered: $M_1 = T$ – teacher model; $M_2 = S$ – standard distilled student model; $M_3 = S^*$ – proposed behavioural-aware transfer learning model;

5.1. Evaluation Metrics

Risk assessment accuracy was evaluated using Accuracy and F1-score metrics:

$$A_{cc} = \frac{N_c}{N}, F_1 = \frac{2PR}{P+R} \quad (18)$$

where P and R denote precision and recall, respectively.

To evaluate the preservation of structured risk knowledge after knowledge distillation, the following indicator was used:

$$C_r = 1 - \frac{|R_T - R_S|}{R_T} \quad (19)$$

which characterizes the consistency of predictions between the teacher and student models.

5.2. Experimental Results

The results of the comparative study are presented in Table 1.

Table 1 – Comparison of road risk assessment models

Model	Accuracy	F1	Latency (ms)	Risk Consistency
Teacher	95.2	0.94	76	1.00
Student	91.8	0.90	31	0.87
Proposed	94.6	0.93	34	0.96

Analysis of the results shows that the traditional student model partially loses risk-sensitive knowledge after compression, which reduces the accuracy of assessing borderline and critical scenarios [7, 16].

The proposed behavioural-aware transfer learning approach significantly reduces these losses and brings the performance of the compact student model closer to that of the teacher solution while maintaining low inference latency.

This is particularly evident for scenarios of the Suspect and Unsafe classes, where the incorporation of behavioural features significantly improves the stability of risk prediction.

The results indicate the feasibility of transitioning from the traditional model $Risk = f(O)$ to the extended risk model $Risk = f(O, B)$, in which the behavioural characteristics of traffic participants constitute a significant source of information for risk assessment.

5.3. Discussion

The obtained results indicate that the proposed approach has advantages compared to classical object-centric and standard distillation models.

In contrast to traditional knowledge distillation approaches [7–9], the proposed method transfers not only feature-level knowledge but also behavioural risk representations through the L_{beh} component in the training loss functional.

This allows knowledge distillation to be interpreted not merely as model compression, but as the transfer of structured behavioural risk representations [10-12].

From an applied perspective, the results confirm the suitability of the software system for online deployment on resource-constrained edge devices.

However, the accuracy of behavioural features depends on the stability of trajectory estimation and object interaction scenarios, which defines the direction for future research.

6. Conclusions

In this work, a transfer learning software system for road risk assessment based on object and human behavioural features has been developed, aimed at online analysis of road scenes under limited computational resources.

Within the framework of the study, a road scene representation model combining object-based and behavioural features is proposed, as well as a mathematical risk assessment model based on the Safe–Suspect–Unsafe classes.

A teacher–student transfer learning model with a behaviour-aware loss function$L = \alpha L_{det} + \beta L_{feat} + \gamma L_{beh} + \delta L_{risk}$ has been developed, which, unlike traditional knowledge distillation approaches, ensures the transfer of risk-oriented behavioural knowledge.

A software system architecture and an online road risk monitoring algorithm for resource-constrained edge devices are proposed.

Experimental results demonstrate that the use of behavioural-aware transfer learning improves risk assessment accuracy, enhances the detection of critical scenarios, and ensures high consistency of predictions after knowledge distillation.

The results indicate the feasibility of using object and human behavioural features in software systems for road risk assessment and the promise of combining transfer learning with risk-oriented scene reasoning for intelligent transportation systems.

Future research should be directed toward the integration of prototype-oriented monitoring and reliability-aware transfer learning.

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