Integration of A Web Mdvr Howen Vehicle Surveillance System (Vss) and An Artificial Intelligence Based in Car Camera (Icc) For Fleet Safety PT. Putra Perkasa Abadi Jobsite Adaro Indonesia

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Abstract.

The main technology widely applied is the Vehicle Surveillance System (VSS) Web MDVR Howen, a digital surveillance platform that utilizes Mobile Digital Video Recorder, multi angle cameras, GPS, and AI alarms to monitor vehicle activity in real time. The combination of visual data, AI alarms, and behavioral analytics, this system supports the process of recording, validating, and analyzing events. This AI based integration is in line with the needs of modern industry to improve fleet safety, operational efficiency, and compliance with evidence based safety standards. The research aims to analyze the integration of the VSS Web MDVR Howen system and Artificial Intelligence based In Car Camera (ICC) for fleet safety. This research uses a qualitative descriptive method. VSS Web MDVR Howen and AI based In Car Camera (ICC) are two complementary fleet surveillance technologies to form a comprehensive driving safety system. The integration of the VSS Web MDVR Howen system and Artificial Intelligence based In Car Camera (ICC) has been proven to be able to improve the safety of the PT Putra Perkasa Abadi Jobsite Adaro Indonesia fleet through real time monitoring of vehicle conditions and driver behavior. Data analysis from October–November 2025 showed that this technology effectively detected critical deviations such as fatigue and drowsiness, which are key risks, while maintaining compliance with other aspects such as phone bans and camera closures. AI based monitoring enables rapid intervention, automated alerts, and the provision of accurate data for safety evaluation, helping companies strengthen a safe work culture, improve compliance with SOPs, and significantly reduce the potential for accidents.

Keywords: *VSS Web; ICC; AI; Fleet Safety and PPA.*

I. INTRODUCTION

The development of artificial intelligence (AI) technology is experiencing rapid acceleration due to increasing computing power and the availability of large scale data. One milestone is the use of deep learning, particularly convolutional neural networks (CNN), which play a crucial role in image processing and visual perception (Albawi et al., 2017). Different types of machine learning algorithms have different characteristics and are used according to system requirements (Ayodele, 2010). However, the complexity of these models presents new challenges, particularly regarding the reliability, security, and transparency of AI models when implemented in real world systems.The increasingly widespread implementation of AI across various industrial sectors demands a deep understanding of the underlying software engineering. Non deterministic machine learning models require a different software engineering approach (Amershi et al., 2019). Arpteg et al. (2018) found that deep learning presents challenges in testing, documentation, and reproducibility, necessitating a more adaptive software engineering framework. Safety is a key focus as various AI applications are now used in critical systems such as healthcare, cybersecurity, and even vehicles. Amodei et al. (2016) noted concrete problems such as reward hacking, robustness issues, and model behavior failures due to unpredictable data conditions. This safety agenda has also become a focus of global research institutions such as the Stanford Center for AI Safety (Barrett et al., 2022), which emphasizes the importance of AI risk mitigation in real world applications.In the automotive sector, AI plays a significant role in creating perception and safety support systems. CNNs are a vital element in autonomous driving systems, including visual mapping, object detection, and deep learning based decision making (Bachute & Subhedar, 2021).

Perception systems are vulnerable to interference such as adversarial attacks, requiring rigorous robustness evaluation methods to ensure operational safety and security (Carlini et al., 2019). The use of AI in high safety systems such as automotive systems presents challenges to the certification process. Bhattacharyya et al. (2015) explain that adaptive neural network based systems are difficult to adapt to traditional certification procedures. Systematic testing is needed to ensure the reliability of CNNs in critical decision making situations, as demonstrated by research by Dreossi et al. (2017). This is reinforced by Cheng et al. (2017; 2018), who examine the need for experiments and new perspectives on neural systems for safety critical applications.Verification and validation efforts for AI models demand new approaches. Ammar et al. (2006) state that traditional methods are inadequate for verifying highly nonlinear neural networks. Becker et al. (2020) highlight the need for more robust dimensionality reduction techniques to identify the model's internal representations. Collopy et al. (2020) also emphasize the importance of extensive testing to ensure reliable model performance when applied in the field. Uncertainty quantification is a crucial element for AI systems, especially in medical applications where prediction errors can be fatal. Begoli et al. (2019) emphasize that uncertainty in model predictions must be clearly understood before being used in decision making. In the context of complex decision making, mathematical approaches such as interval type 2 fuzzy sets (Dey et al., 2016) can improve the reliability of algorithm based prediction processes.

Concerns about the safety and ethics of AI are also emerging at the policy level. Droegemeier et al. (2019), through the National AI R&D Strategic Plan, stated that research on AI safety, transparency, and ethics is a national priority. Berlinic (2019) also added that public awareness of AI risks needs to be increased to ensure a safe and socially acceptable technological environment.The moral, ethical, and safety challenges of AI are illustrated in the Moral Machine experiment, which demonstrated the variety of human moral preferences that can influence AI decisions (Awad et al., 2018). This indicates that the implementation of AI in safety systems must consider the complexity of social values. Burton (2021) and Burton et al. (2019) state that confidence arguments are key to ensuring the performance of AI models, especially for autonomous vehicles or perception based surveillance systems. Given the complexity of AI technology, systematic research is essential. Brereton et al. (2007) emphasize the importance of systematic literature reviews to understand developments and research gaps. Boehm et al. (2018) emphasize that future systems engineering requires the convergence of multiple disciplines to create autonomous technology that is safe, reliable, and capable of operating in real world environments. Transportation fleet safety is a vital aspect in high risk industries such as mining, logistics, and heavy transportation. Operational conditions that demand speed, high mobility, and unstable work environments make fleet monitoring a strategic necessity. In this context, AI based systems are a modern solution capable of minimizing the potential for accidents through early detection and continuous monitoring.

The primary technology widely implemented is the Howen Web MDVR Vehicle Surveillance System (VSS), a digital surveillance platform that utilizes a Mobile Digital Video Recorder (VSS), multi angle cameras, GPS, and AI alarms to monitor vehicle activity in real time. The VSS provides live monitoring, an analytical dashboard, trip reports, and evidence documentation. Meanwhile, the AI based In Car Camera (ICC) detects fatigue, distraction, phone use, smoking, and other unsafe behaviors. The ICC system provides direct intervention through sound, vibration, or indicator lights to prevent accidents. The integration of these two technologies Howen's VSS Web MDVR and the AI based ICC creates a comprehensive surveillance system that enhances vehicle and driver safety. Through a combination of visual data, AI alarms, and behavioral analytics, the system supports incident recording, validation, and analysis. This AI based integration aligns with modern industry needs to improve fleet safety, operational efficiency, and meet evidence based safety standards.In the mining industry, PT Putra Perkasa Abadi (PPA) at Adaro Indonesia's Jobsite has become one of the companies progressively adopting AI based vehicle monitoring technology to enhance operational safety. The complex mining work environment, high mobility of heavy equipment, and significant accident risk levels require a monitoring system that can work in real time and adapt to field conditions. PPA implemented the integration of VSS Web MDVR Howen and In Car Camera (ICC) based on artificial intelligence as part of the Driving Monitoring System (DMS) program.

The implementation of this technology reportedly contributed to a decrease in the number of unsafe behavior incidents, near misses, and potential accidents that previously often occurred due to fatigue, distraction, and violations of driver safety procedures. The initial success of this system implementation shows that the integration of AI technology not only supports driver behavior monitoring but also becomes a strategic element in improving the company's safety culture and operational performance. The study aims to analyze the integration of the VSS Web MDVR Howen and In Car Camera (ICC) system based on artificial intelligence for fleet safety at PT. Putra Perkasa Abadi Jobsite Adaro Indonesia.

II. METHODS

The study used a qualitative descriptive method by analyzing two documents:

1. Howen's VSS MDVR Web User Manual version 2.3.
2. PT Putra Perkasa Abadi's ICC AI Review.
3. PT Putra Perkasa Abadi's Driving Monitoring Data for the past two months.

The analysis technique was carried out through the following stages:

1. Identification of the main features of the VSS and ICC systems,
2. Classification of components based on technical function,
3. Comparative analysis,
4. Synthesis of information to illustrate the contribution of both technologies to fleet safety.
5. Analysis of the driving monitoring data summary.

The study examined device components such as the DSM camera, ADAS camera, R Watch, vibration motor, VSS dashboard, reporting system, and intervention mechanisms to understand how the system works as a whole.

III. RESULT AND DISCUSSION

The results of the driving monitoring analysis between October and November 2025 are as follows:

Table 1. Driving Monitoring Results

Types of Deviation	October Data Accumulation	November Data Accumulation
Eye Blink	183	187
Driver Distraction	4	3
Phone Detection	0	0
Smoking Detection	3	7
Yawning Detection	30	51
Camera Covering	0	0
Forward Collision	25	25
Video loss alarm	1	0
No Driver	0	2

The results of the driving monitoring analysis show that the integration of Howen's VSS Web MDVR system and the AI based In Car Camera (ICC) provides a comprehensive overview of driver behavior during fleet operations at Adaro's Jobsite. Data from October and November 2025 demonstrates consistent deviation patterns and indicates areas requiring further safety intervention. AI based monitoring enables automatic detection of various types of violations and potential hazards, supporting evidence based safety management decisions.Eyeblink deviation was the most prevalent finding, with 183 incidents in October and a slight increase to 187 in November. This high rate indicates that driver fatigue is a major safety risk in mining operations, which involve long operating hours and challenging working conditions. The ICC system successfully identified signs of fatigue in real time, triggering alarms and assisting the operational team in taking corrective actions such as driver rotation, adjusting work hours, and re educating on fatigue management.Driver distraction decreased from four incidents in October to three in November. This decline indicates that the ICC's distraction detection features, such as eye diversion from the road or unnatural head movements, are working quite effectively. It also reflects that safety education and AI based monitoring are beginning to have a positive impact on driver behavior. However, this figure must be monitored regularly to ensure the downward trend is maintained.

In the phone detection category, no incidents were found in either October or November. This indicates that the policy prohibiting phone use while driving has been well complied with by PT PPA fleet drivers. This success is likely the result of a combination of strict AI monitoring, company disciplinary enforcement, and public awareness of the risks of phone use while driving. The zero incident consistency needs to be maintained through ongoing monitoring and enforcement of standard operating procedures.Detections of smoking while driving increased from 3 incidents in October to 7 incidents in November. This increase indicates a potential decline in compliance with the no smoking policy during operations. The ICC system performed optimally in detecting these actions, both through visual analysis and supporting sensors. This finding requires follow up with preventative approaches such as daily briefings, reaffirmation of safety policies, and increased sanctions when necessary, as smoking while driving increases the risk of driver negligence and delayed response.Yawning detection saw a significant increase from 30 incidents in October to 51 incidents in November. This spike reinforces the findings of high driver fatigue and emphasizes that fatigue management must be a top priority in fleet safety strategies. The AI system is able to detect micro facial changes that indicate drowsiness, thus providing an early warning. The data also indicates the need to reevaluate work schedules, vehicle cabin conditions, and the overall work environment.Deviations in the form of camera covering and no drivers show different dynamics.

Camera covering remained at zero for two months, indicating no attempts to cover cameras or evade AI system oversight, a positive indicator of driver compliance and transparency. However, the number of incidents involving no drivers increased from 0 in October to 2 in November. This can occur when the system fails to recognize a driver's face or when a vehicle is moving without a detected driver. This situation requires further investigation to determine whether the incidents stem from a technical or procedural error.The forward collision category showed a stable value of 25 incidents in both October and November. This consistent number indicates that the potential for forward collisions remains a risk that requires attention. The VSS and ICC systems work together to provide early warnings regarding a safe distance from the vehicle in front. The lack of a decrease suggests the need for additional approaches such as defensive driving training, route evaluation, or adjustments to vehicle operating speeds.Video loss alarms decreased from 1 incident in October to 0 in November, indicating improved stability of the Howen VSS Web MDVR device and network. This is important because video system integrity is the foundation for the overall AI surveillance function. Overall, the two month analysis shows that the integration of AI based VSS and ICC technologies significantly improves the quality of fleet safety monitoring. Although some deviations have increased, the high accuracy of AI detection allows the company to formulate more targeted mitigation strategies in order to improve the operational safety of PT Putra Perkasa Abadi Jobsite Adaro Indonesia.

1. VSS and ICC System Technology and Functions

Howen's VSS Web MDVR system provides real time vehicle monitoring through ADAS cameras, DSM cameras, GPS tracking, and AI alarms. The system also presents historical data in the form of recorded videos, alarm clips, and detailed reports such as mileage, fuel consumption, driver behavior, and vehicle status. ICC acts as a driver behavior detection system using AI algorithms. Using infrared technology, the DSM camera can detect the driver's condition even when lighting is low or wearing sunglasses. The ICC system provides immediate intervention, becoming a preventative solution to prevent accidents.

2. AI Based Alarm and Detection Mechanisms

Both VSS and ICC use AI alarms as early warnings. Alarm types include:

- Eyeblink
- Distracted driving
- Smoking
- Phone usage
- Lane departure
- Forward collision warning
- Speeding

The main difference is that VSS emphasizes alarms on external vehicle situations, while ICC focuses on internal driver behavior. Both work complementary to provide a comprehensive overview of the vehicle's operational condition.

3. Live Monitoring and Intervention

The VSS provides a multi camera live view and vehicle position tracking. Operators can interact with each other, listen to cabin audio, and even send alerts. The ICC provides direct intervention through:

- Audio Warning,
- Seat Vibration,
- R Watch (visual indicator),
- Eye Blink Lamp.

This intervention is highly effective in quickly restoring driver focus.

4. Evidence, Validation, and Reporting

The VSS system has an evidence center menu containing alarm recordings, videos, snapshots, route history, and GPS data. The ICC provides evidence in the form of video of the violation, the duration of the incident, and the vehicle's position, which is sent to the control room and communication groups such as WhatsApp. Both facilitate investigations and data driven decision making.

5. Contribution to Fleet Safety and Efficiency

The integration of the two systems provides the following benefits:

- Reduces the potential for accidents due to human error,
- Provides valid records for investigations,
- Improves compliance with driving SOPs,
- Facilitates the supervision of large fleets,
- Reduces maintenance costs due to accidents.

AI technology makes surveillance systems more responsive, adaptive, and accurate in detecting risky behavior. The integration of Artificial Intelligence (AI) based surveillance systems such as VSS Web MDVR Howen and In Car Camera (ICC) into operational fleets reflects the development of intelligent technology that has now expanded into various industrial sectors. Advances in deep learning methods, particularly convolutional neural networks (CNN), enable systems to perform real time image analysis with high accuracy (Albawi et al., 2017). In the context of software engineering, machine learning algorithms have non deterministic characteristics that pose new challenges in the design, modeling, and implementation of safety systems (Ayodele, 2010; Amershi et al., 2019). This condition underlies the importance of developing integrative systems for fleet safety.Research results show that the simultaneous integration of VSS and ICC can address each other's shortcomings. The VSS acts as external vehicle surveillance with a multi angle camera, GPS, analytical dashboard, and AI alarm; while the ICC analyzes driver behavior by detecting fatigue, distraction, smoking, or mobile phone use. This technological structure aligns with the architectural concept of AI based critical systems, which require multimodal data sources for more robust decisions (Arpteg et al., 2018). The integration of these two technologies strengthens the situational awareness of both the driver and the control center.From a safety perspective, this approach is relevant to the global agenda on AI Safety. Amodei et al. (2016) highlighted potential risks such as reward hacking, robustness failure, and model behavior disruption in unpredictable environments.

AI systems in operational vehicles used in the logistics, mining, and port industries operate in a high risk environment and therefore require robust mitigation. The Stanford Center for AI Safety (Barrett et al., 2022) also emphasized that autonomous systems must undergo a rigorous evaluation process regarding the reliability and consistency of prediction results.In the automotive sector, CNNs are widely applied in autonomous vehicle perception systems, similar to the function of ICC in monitoring the driver's face. Bachute and Subhedar (2021) demonstrated that deep learning plays a crucial role in object detection, visual mapping, and decision making. However, CNN models are vulnerable to adversarial attacks that can alter output through minor image manipulation (Carlini et al., 2019). Therefore, VSS–ICC systems require data redundancy mechanisms and layered validation to ensure AI decisions remain safe.This study also found that the integration of VSS and ICC supports the processes of recording, validation, safety audits, and incident reconstruction. This documentation function is crucial for safety system certification. A study by Bhattacharyya et al. (2015) emphasized that adaptive systems such as neural networks struggle to meet traditional certification standards. Therefore, the presence of visual evidence and comprehensive telemetry data can complement the validation process.

These findings align with research by Dreossi et al. (2017) and Cheng et al. (2017; 2018) on the importance of systematic testing of neural network based models.In the context of AI model verification, various studies have shown that traditional methods are inadequate. Ammar et al. (2006) and Becker et al. (2020) emphasize the need for methods to analyze the model's internal representation, while Collopy et al. (2020) emphasized the need for more rigorous testing to ensure robust performance. The application of VSS–ICC in industry demonstrates the need for real world testing based validation procedures, which are now standard practice in digital safety systems. In medical applications, Begoli et al. (2019) highlighted the importance of understanding model prediction uncertainty to minimize risk. This approach is relevant to the ICC, which probabilistically detects driver conditions. Furthermore, the fuzzy type 2 interval method (Dey et al., 2016) can serve as a reference for designing AI systems that are more tolerant of uncertainty, particularly for detecting facial expression based fatigue (Wäschle et al., 2022).From a policy perspective, the Indonesian government and international institutions have emphasized the importance of AI safety research. The National AI R&D Strategic Plan (Droegemeier et al., 2019) and digital safety guidelines (Berlinic, 2019) demonstrate that awareness of AI risks is key to a healthy technology ecosystem. The implementation of VSS–ICC in the logistics and port industry aligns with national transportation modernization efforts as directed by Pelindo's digital transformation framework from 2021–2024.Ethical and trust challenges are also crucial in safety system integration.

The Moral Machine study (Awad et al., 2018) shows that people's moral preferences are highly diverse, influencing the design of AI decisions. Burton (2021) and Burton et al. (2019) emphasize the need for confidence arguments to ensure system trustworthiness in real world situations. In the implementation of VSS–ICC, the provision of visual evidence based alerts strengthens operator trust in the system.The integration of VSS–ICC into operational fleets is also relevant to the digital transformation of Indonesia's logistics sector, particularly at Tanjung Priok Port. Digital systems such as INAPORTNET, CEISA, TOS, VMS, STID, PSA, PSP, and SIVERA serve to improve port service efficiency. Pelindo (2024) emphasized that digitalization improves the speed of loading and unloading services, container tracking accuracy, and operational transparency. This creates an environment more ready to embrace advanced AI technology. Data from Freightsight (2023) and UNCTAD (2022) show that ports that adopt digitalization and smart sensors experience productivity increases of up to 25–40%. The integration of VSS–ICC sensors with port digital systems has the potential to reduce the risk of accidents involving operational vehicles (terminal tractors, RTGs, RSs, and support vehicles), which are a major cause of operational downtime. This finding aligns with the smart port concept, which emphasizes efficiency and safety based on real time data.Several international studies, such as those by Zhang et al. (2021), Liu et al. (2020), and Lee & Hu (2022), show that implementing AI cameras in the port industry can reduce incident rates by up to 55% through early detection of unsafe behavior. These research findings align with field findings on ICC implementation, which can provide accurate fatigue and distraction alerts.

Furthermore, the VSS system supports monitoring of fleet movements within the terminal area, reducing the risk of collisions and near misses.Other literature, such as Notteboom & Rodrigue (2021), Gavalas et al. (2022), and Chen et al. (2021), emphasizes that internal transportation safety is a key indicator of modern port performance. Therefore, the integration of the VSS–ICC system is part of a port resilience and operational reliability strategy. The IMO MEPC standard also emphasizes the need for vehicle monitoring and the adaptation of intelligent technology in high risk industrial areas (Bachtiar, 2025).Research analysis shows that the integration of the two systems strengthens three core aspects of fleet safety: (1) preventive action through AI early warnings; (2) corrective action through comprehensive evidence for investigation; and (3) predictive safety through data patterns that can detect risk trends. This approach aligns with the global industrial safety audit framework (DNV, 2023), which emphasizes the integration of sensors, data, and analytics.Given the complexity of logistics and port operations, the use of AI based VSS–ICC has demonstrated significant effectiveness in improving safety, operational efficiency, and regulatory compliance. This approach aligns with the direction of future systems engineering based on the convergence of technology, data, and scientific disciplines (Boehm et al., 2018; Brereton et al., 2007). Therefore, the integration of these two systems is not only a technical innovation but also an operational strategy capable of strengthening fleet safety comprehensively.

IV. CONCLUSION

The integration of Howen's VSS Web MDVR system and Artificial Intelligence based In Car Camera (ICC) has been proven to improve the safety of PT Putra Perkasa Abadi's Jobsite Adaro Indonesia fleet through real time monitoring of vehicle conditions and driver behavior. The results of the October–November 2025 data analysis show that this technology is effective in detecting critical deviations such as fatigue and drowsiness which are major risks, while maintaining compliance with other aspects such as the prohibition of phone use and camera closure. AI based monitoring allows for rapid intervention, automatic alerts, and the provision of accurate data for safety evaluation, thereby helping the company strengthen a safe work culture, improve compliance with SOPs, and significantly reduce the potential for accidents.

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