Final Report

AMPC
AUSTRALIAN MEAT PROCESSOR CORPORATION

SafePassAI

AI-Powered Hygiene & Safety Compliance Monitoring

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1.0 Abstract

SafePassAI is an applied research and development project focused on the use of artificial intelligence and computer vision to support hygiene and safety compliance monitoring within meat processing environments. The project was developed to address the limitations of manual compliance monitoring in operational settings where high personnel movement, visual occlusion, repetitive workflows, and continuous production activity can make reliable observation difficult.

The project investigated whether AI-assisted monitoring could provide continuous, objective, and scalable compliance insights across key hygiene and safety workflows, including personnel localisation, personal protective equipment monitoring, boot sanitisation assessment, and handwashing behaviour analysis. The system was developed using a hybrid architecture that combines edge-based AI processing with centralised analytics, allowing operational events to be interpreted at a behavioural and session level rather than as isolated detections.

Through progressive development, testing, and refinement under real-world operational conditions, the project demonstrated that AI-based behavioural compliance monitoring can be practically applied in complex industrial environments. The system showed the ability to generate structured compliance insights, support operational review, and provide evidence-based visibility of hygiene and safety workflows.

The project outcomes indicate that AI-assisted compliance monitoring has potential to improve operational awareness, support more consistent hygiene and safety processes, reduce reliance on fully manual observation, and provide a scalable foundation for future intelligent monitoring applications across the meat processing industry.

2.0 Executive summary

The SafePassAI project was undertaken to explore how artificial intelligence and computer vision can support hygiene and safety compliance monitoring within meat processing facilities. These environments present practical monitoring challenges due to high personnel density, repetitive movement, visual obstruction, and continuous operational activity. Traditional compliance monitoring methods often rely on manual observation, which can be labour-intensive, inconsistent, and difficult to scale across busy processing environments.

The project focused on developing and validating an AI-assisted monitoring framework capable of analysing key hygiene and safety workflows in near real time. The core objective was to determine whether computer vision, multi-camera analysis, behavioural interpretation, and operational reporting could be combined into a practical system suitable for industrial use. The target audience for the project includes meat processors, food safety and quality assurance teams, operational managers, technology providers, and industry stakeholders interested in improving compliance visibility and operational monitoring.

The project developed a modular AI platform capable of supporting multiple compliance-related workflows, including personnel localisation, PPE monitoring, boot sanitisation assessment, and handwashing behaviour analysis. Rather than relying only on isolated object detection, the project adopted a behavioural monitoring approach in which observations are interpreted over time and associated with operational sessions. This enabled the system to provide more meaningful compliance insights than simple frame-by-frame detection outputs.

The methodology combined edge-based AI processing with centralised analytics. Edge devices performed initial visual analysis and region-of-interest extraction, while central processing enabled higher-level behavioural interpretation, event aggregation, compliance scoring, and reporting. This hybrid approach was selected to balance real-time performance, scalability, and the practical limitations of deploying AI within industrial environments.

The project was delivered progressively across multiple development phases. Early work established the hardware, data processing, and localisation foundations. Subsequent phases introduced PPE monitoring, boot sanitisation analysis, and handwashing behavioural assessment. The final stage focused on integration, operational validation, system refinement, and evaluation under live industrial conditions.

The results demonstrated that AI-assisted behavioural compliance monitoring can operate practically in complex processing environments when supported by appropriate system design, multi-camera context, iterative refinement, and operationally focused workflows. The system was able to provide structured compliance information, support review of hygiene and safety events, and demonstrate the practical value of transforming conventional video monitoring into a more intelligent operational support tool.

The project also highlighted several important implementation lessons. Practical deployment depends not only on AI model accuracy, but also on camera positioning, environmental observability, data quality, behavioural aggregation, system usability, and the ability to refine the system over time. The findings showed that industrial AI systems must be designed as complete operational platforms rather than standalone detection models.

The key benefits to industry include improved visibility of hygiene and safety workflows, reduced dependence on manual monitoring, more consistent compliance review, improved operational awareness, and the creation of structured evidence to support training, process improvement, and future audit activities. The project also demonstrated potential for broader application beyond hygiene monitoring, including safety workflow analysis, procedural compliance, and operational performance monitoring.

Future work should focus on continued dataset expansion, refinement of behavioural analysis methods, privacy-conscious identity association approaches, further operational validation across additional environments, and exploration of wider industrial use cases. The project provides a scalable foundation for future AI-assisted compliance and operational intelligence systems within the meat processing industry.

3.0 Introduction

Hygiene and safety compliance are essential requirements within meat processing environments. Facilities must maintain consistent procedures relating to personal protective equipment, sanitation, hand hygiene, and safe movement through operational areas. While these procedures are well understood, monitoring them continuously and consistently in active processing environments remains challenging.

Processing facilities are dynamic environments. Personnel may move through confined areas, perform repetitive tasks, interact with shared hygiene stations, and operate within spaces where visibility can be limited by equipment, workflow layout, and other people. In these conditions, manual monitoring can be difficult to sustain and may not provide continuous, objective, or traceable evidence of compliance behaviour.

The SafePassAI project was established to investigate whether artificial intelligence and computer vision could provide a practical method for supporting hygiene and safety compliance monitoring in these environments. The project explored the use of visual analytics, behavioural interpretation, and operational reporting to assist facilities in understanding whether key compliance actions are being performed and how those actions can be reviewed over time.

The project was informed by established work in computer vision, multi-object tracking, hand hygiene guidance, and edge-based AI deployment. However, the focus of SafePassAI was not limited to laboratory model development. The project was designed as an applied industrial research activity, with emphasis on practical deployment, operational robustness, user accessibility, and the ability to function within real processing conditions.

The main research question addressed by the project was whether AI-assisted monitoring could move beyond simple object detection and support higher-level interpretation of hygiene and safety behaviours. This included determining whether the system could identify personnel movement, associate compliance-related observations with operational sessions, interpret behaviours over time, and provide reviewable outputs suitable for operational use.

The target audience for the project includes meat processing businesses, food safety teams, quality assurance personnel, operations managers, industry technology providers, and stakeholders seeking practical tools for improving compliance visibility and operational decision-making. The results are intended to inform future adoption of intelligent monitoring systems within the meat processing industry and related industrial environments.

A key feature of the SafePassAI approach was the use of a modular architecture. Rather than creating a single-purpose monitoring tool, the project developed a framework capable of supporting multiple compliance workflows. This included personnel localisation, PPE monitoring, boot sanitisation assessment, and handwashing behaviour analysis. The modular approach allows different analytical capabilities to be refined, extended, or adapted to future use cases.

The project also investigated the role of AI-assisted monitoring as a support tool rather than a replacement for operational management. The intention was to provide improved visibility, structured evidence, and actionable insights that can assist staff training, compliance review, process improvement, and future decision-making.

Overall, SafePassAI represents an applied research effort focused on translating AI and computer vision methods into a practical operational framework for hygiene and safety compliance monitoring within the meat processing sector.

4.0 Project objectives

The overall objective of the SafePassAI project was to design, develop, and validate an AI-assisted computer vision platform capable of supporting hygiene and safety compliance monitoring in meat processing environments.

The project aimed to determine whether visual analytics and behavioural interpretation could provide practical, scalable, and reviewable compliance insights within live industrial workflows. The objectives were delivered progressively through a staged development approach.

4.1 Establish a Monitoring and Processing Foundation

The initial objective was to establish the technical foundation required for AI-assisted monitoring. This included deployment of suitable camera infrastructure, preparation of the processing environment, establishment of communication pathways, and development of the baseline architecture required for later analytical modules.

This phase provided the infrastructure required for real-time data capture, event generation, and future system integration.

4.2 Develop Personnel Localisation and Tracking Capability

A core objective of the project was to enable the system to detect and track personnel movement within monitored operational areas. This capability was required so that compliance-related events could be associated with personnel sessions rather than treated as disconnected visual observations.

The localisation and tracking framework provided the foundation for all later compliance modules, including PPE monitoring, sanitation assessment, and handwashing analysis.

4.3 Develop PPE Monitoring Capability

The project aimed to develop an AI-assisted method for monitoring personal protective equipment compliance in operational environments. This included identifying relevant PPE indicators, associating observations with tracked sessions, and generating outputs suitable for operational review.

The objective was not only to detect equipment, but also to integrate PPE observations into a broader compliance monitoring workflow.

4.4 Develop Boot Sanitisation Monitoring Capability

Another objective was to assess whether AI-assisted monitoring could support evaluation of boot sanitisation behaviour. The project investigated practical methods for determining whether personnel interacted with sanitisation areas in a manner consistent with expected hygiene procedures.

This objective required a behavioural interpretation approach based on spatial presence, time-based analysis, and association with tracked personnel sessions.

4.5 Develop Handwashing Behavioural Analysis Capability

The project also aimed to develop a method for analysing handwashing behaviour. This represented a more complex behavioural monitoring task because handwashing involves a sequence of actions rather than a single location-based event.

The objective was to determine whether handwashing activity could be analysed at a session level, allowing the system to assess duration, behavioural coverage, and overall compliance-related indicators.

4.6 Integrate Analytics into an Operational Platform

A major objective was to integrate the individual analytical modules into a unified operational platform. This included event processing, behavioural aggregation, reporting, user interface development, and integration with existing video monitoring workflows.

The goal was to ensure that the system operated as a practical tool for operational review rather than a collection of isolated AI models.

4.7 Validate Practical Deployment and Industry Relevance

The final objective was to validate the system under real-world operational conditions and assess its relevance for industry adoption. This included evaluating stability, usability, system refinement needs, and the potential value of AI-assisted monitoring for hygiene and safety compliance workflows.

The project also sought to identify future research and development opportunities arising from the deployment, including broader behavioural monitoring, privacy-conscious identity association, and extension to additional industrial use cases.

5.0 Methodology

The SafePassAI project used an iterative applied research and development methodology. The project was not limited to developing individual AI models; instead, it focused on designing, integrating, testing, and refining a complete operational monitoring framework suitable for real industrial environments.

The methodology combined computer vision, edge-based AI processing, centralised analytics, behavioural interpretation, event aggregation, and operator-facing reporting. Development was conducted progressively across project phases, with each phase building on the technical foundations established in earlier stages.

A key methodological principle was to prioritise practical operational reliability. Meat processing environments present real-world challenges such as visual obstruction, personnel overlap, lighting variation, equipment interference, and continuous movement. For this reason, the project emphasised field-based validation, iterative refinement, and session-level interpretation rather than relying solely on laboratory-style model performance.

5.1 Hybrid AI Architecture

The project adopted a hybrid AI architecture combining edge-based processing with centralised analytics.

Edge-based processing was used to perform initial visual analysis close to the camera source. This helped reduce unnecessary data transfer and allowed specific camera views to support specialised analytical tasks.

Centralised analytics were used for higher-level interpretation, including tracking, behavioural aggregation, compliance scoring, reporting, and evidence review. This approach enabled the system to combine information over time and across multiple camera views.

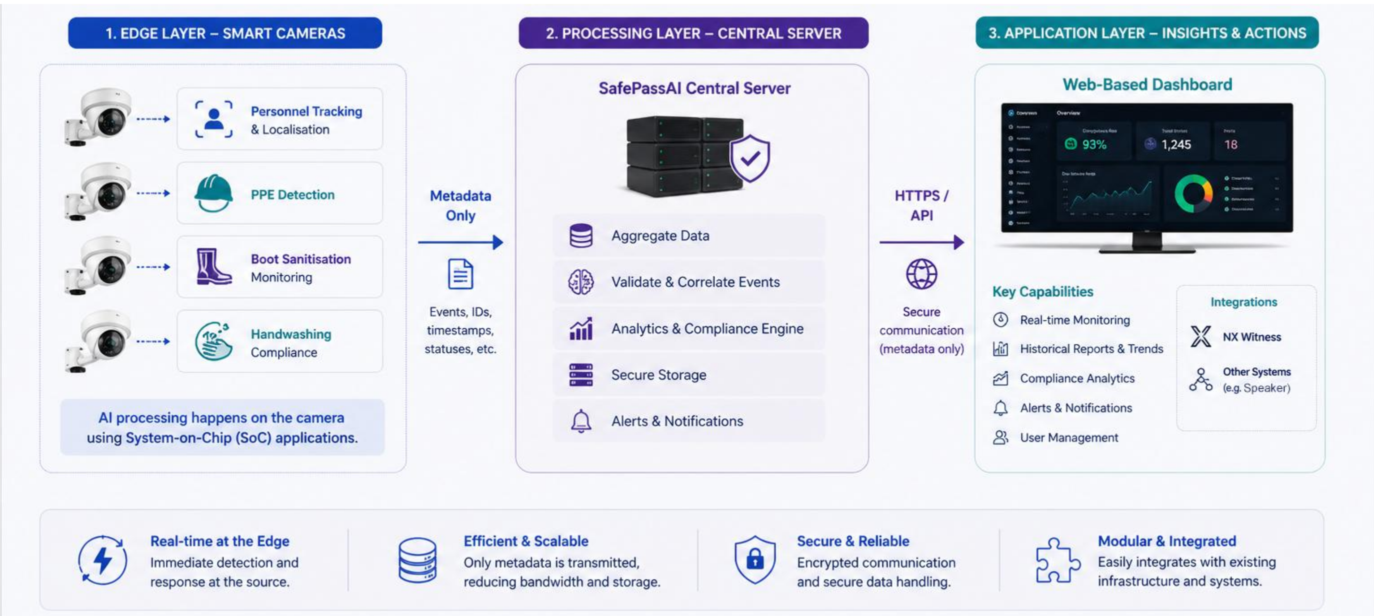

Figure 5.1.1 – SafePassAI hybrid AI architecture. Edge-based camera applications perform initial detection and region-of-interest extraction, while centralised analytics perform multi-camera tracking, behavioural aggregation, compliance scoring, reporting, and Video Management System integration.

The hybrid architecture provided several practical advantages:

- reduced processing load on individual devices,

- improved scalability across multiple monitoring points,
- flexibility for future analytical modules,
- centralised management of compliance logic,
- and improved ability to generate structured reporting outputs.

This architecture was selected because fully edge-based processing would limit behavioural interpretation capability, while fully centralised processing would increase infrastructure and bandwidth demands. The hybrid approach provided a practical balance between real-time performance and system-level intelligence.

5.2 Multi-Camera Monitoring Methodology

The project used a multi-camera monitoring methodology to improve visibility and support behavioural interpretation across operational workflows.

Rather than relying on a single camera view, the system combined observations from multiple viewpoints. This approach helped address common challenges in industrial environments, including partial occlusion, overlapping personnel, and limited visibility in specific areas.

Multi-camera analysis supported:

- personnel localisation,
- tracking continuity,
- association of compliance events with operational sessions,
- and improved interpretation of behaviour across different activity zones.

The methodology allowed individual observations to be combined into a broader operational understanding. This was important because compliance behaviours such as PPE use, boot sanitisation, and handwashing may occur across different physical areas and time periods.

5.3 Personnel Localisation and Tracking

Personnel localisation and tracking formed the foundation of the SafePassAI methodology.

The purpose of tracking was to enable the system to associate compliance-related observations with personnel sessions over time. Without tracking, PPE observations, sanitation events, and handwashing behaviours would remain disconnected and difficult to interpret meaningfully.

The tracking methodology enabled the system to:

- identify personnel movement through monitored areas,
- maintain session continuity where practical,
- associate multiple compliance events with the same operational session,
- and support later review of hygiene and safety workflows.

The project demonstrated that tracking is essential for behavioural compliance monitoring. Compliance is not only a question of whether an object or action appears in a single frame, but whether a sequence of events occurs in the correct operational context.

Because industrial environments can include crowding and visual obstruction, the tracking methodology was designed to tolerate uncertainty and support practical interpretation rather than assume perfect visibility at all times.

5.4 PPE Monitoring Methodology

The PPE monitoring methodology focused on identifying whether relevant protective equipment indicators could be detected and associated with personnel sessions.

The project used a targeted visual analysis approach to improve reliability. Rather than analysing an entire scene equally, the system focused on regions most relevant to PPE assessment. This allowed the analytical process to reduce irrelevant background information and improve classification focus.

PPE observations were then linked to tracked personnel sessions and included as part of the broader compliance record.

The methodology also allowed for uncertainty. In cases where visibility was insufficient or a reliable classification could not be made, the system was designed to avoid overconfident interpretation. This is an important principle for industrial AI systems, where inaccurate compliance decisions can reduce trust and operational usefulness.

5.5 Boot Sanitisation Monitoring Methodology

Boot sanitisation was assessed using a behavioural inference methodology based on interaction with defined sanitisation areas over time.

The project found that directly recognising detailed lower-body cleaning actions is difficult in busy industrial environments due to occlusion, movement overlap, and limited visibility. A more practical approach was therefore used: assessing whether personnel remained within relevant sanitisation areas for an appropriate duration.

This methodology combined:

- spatial presence,
- dwell-time analysis,
- personnel tracking,
- and session-level interpretation.

The approach allowed the system to infer whether observed behaviour was consistent with expected boot sanitisation procedures without requiring perfect visual recognition of every physical movement.

This was an important methodological finding. In industrial environments, robust behavioural inference can sometimes provide more practical value than attempting highly detailed action recognition under visually constrained conditions.

5.6 Handwashing Behavioural Analysis Methodology

Handwashing analysis represented a more complex behavioural monitoring task because it involves a sequence of actions over time.

The project methodology focused on analysing handwashing activity at a session level rather than treating each visual observation independently. This allowed the system to consider:

- wash duration,
- behavioural sequence,
- stage coverage,
- and overall compliance-related indicators.

The system was designed to evaluate handwashing behaviour using a structured set of hygiene-related stages. Observations were aggregated over time to form a more meaningful interpretation of the session.

This session-based approach was selected because individual frame-level detections may be unreliable or incomplete due to temporary obstruction, hand movement, or variation in how personnel perform washing actions.

The project also adopted a progressive compliance approach. Rather than immediately enforcing highly strict behavioural thresholds during early deployment, the system preserved detailed behavioural information while allowing operational settings to be refined over time. This approach supported practical adoption and allowed future tightening of compliance criteria as the system and workplace processes mature.

5.7 Session-Level Aggregation and Compliance Interpretation

A central part of the methodology was converting low-level AI observations into session-level operational insights.

Individual detections are often insufficient for compliance assessment. For example, a single visual observation may show a person near a hygiene station, but it does not necessarily explain whether the full required behaviour occurred. By aggregating observations over time, SafePassAI could provide a more meaningful compliance interpretation.

Session-level aggregation enabled the system to combine:

- movement history,
- PPE observations,
- sanitisation events,
- handwashing behaviour,
- timing information,
- and supporting review evidence.

This methodology allowed compliance to be assessed as part of an operational workflow rather than as isolated visual events.

5.8 Operational Review and Reporting Methodology

The project also developed reporting and review workflows to make AI outputs useful for operational personnel.

The methodology focused on presenting compliance information in a structured and reviewable format. This included summary information, session-level records, behavioural indicators, and supporting evidence.

The purpose of reporting was not only to identify potential non-compliance, but also to support:

- operational review,
- staff training,
- process improvement,

- audit preparation,
- and future system refinement.

This reflects an important principle of the project: AI-assisted monitoring should support decision-making and improvement rather than operate as a black-box enforcement mechanism.

5.9 Iterative Field-Based Refinement

The project used iterative field-based refinement throughout development and validation.

Operational environments introduce challenges that are difficult to fully predict during early-stage development. As a result, the system was progressively refined based on observations from real deployment conditions.

Refinement activities included:

- improving camera positioning and visibility,
- adjusting analytical assumptions,
- expanding datasets,
- refining behavioural logic,
- improving reporting workflows,
- and addressing operational edge cases.

This iterative process was essential to improving system robustness. The project demonstrated that successful industrial AI deployment depends on continuous adjustment to real operating conditions rather than one-off model development.

5.10 Privacy, Security, and Deployment Considerations

The project methodology included consideration of privacy, security, and operational deployment risks.

Because the system relates to personnel movement and compliance monitoring, the project avoided unnecessary direct identification of individuals in the current deployment. The focus was on behavioural association and operational session analysis rather than personal identity recognition.

Cybersecurity and controlled access were also considered as part of the deployment methodology. The project considered deployment readiness, controlled system access, and operational resilience as part of the broader system design and validation approach.

Future expansion involving identity association should be approached using privacy-conscious methods, clear governance, and appropriate consultation with operational stakeholders.

6.0 Results

The SafePassAI project demonstrated that AI-assisted behavioural compliance monitoring can be applied practically within complex meat processing environments. The project progressed from individual analytical components into an integrated operational framework capable of supporting hygiene and safety compliance review.

The results should be interpreted as applied industrial R&D outcomes rather than laboratory-only benchmark results. The project's value lies in demonstrating practical feasibility, operational integration, behavioural interpretation, and industry relevance under real-world conditions.

6.1 Integrated System Deployment Outcomes

The project successfully delivered an integrated AI-assisted monitoring framework combining personnel localisation, PPE monitoring, boot sanitisation assessment, handwashing behavioural analysis, event aggregation, and operational reporting.

A key outcome was the successful transition from isolated computer vision tasks into a broader operational compliance platform. The system demonstrated that multiple analytical modules can operate together to support structured hygiene and safety monitoring workflows.

The deployment confirmed that AI-assisted compliance monitoring requires more than accurate object detection. Practical value was achieved by combining detection outputs with tracking, behavioural interpretation, time-based analysis, session aggregation, and reviewable reporting.

The system demonstrated stable operation across multiple compliance workflows and provided a foundation for further refinement and future deployment expansion.

6.2 Personnel Localisation and Tracking Results

The localisation and tracking component demonstrated the importance of maintaining continuity across personnel sessions. Tracking enabled the system to associate compliance-related observations with operational movement over time.

This capability supported more meaningful interpretation of compliance behaviour. For example, PPE observations, sanitation interactions, and handwashing activity could be associated with a broader operational session rather than treated as disconnected visual events.

The project demonstrated that tracking in busy industrial environments is challenging due to personnel overlap, visual obstruction, similar clothing, and unpredictable movement patterns. However, the multi-camera and session-based methodology improved the ability to maintain practical tracking continuity under normal operational conditions.

The results confirmed that personnel tracking is a foundational requirement for AI-assisted behavioural compliance monitoring. Without tracking, the system would be limited to isolated detections and would not provide the same level of operational insight.

6.3 PPE Monitoring Results

The project demonstrated that AI-assisted PPE monitoring can support operational compliance visibility within meat processing environments.

The PPE monitoring component was able to identify relevant protective equipment indicators and associate observations with personnel sessions. This allowed PPE compliance information to become part of the wider operational compliance record.

The project also confirmed the importance of uncertainty handling. In real-world environments, personnel overlap, partial visibility, and camera angle limitations can reduce classification confidence. The system was therefore designed to avoid forcing unreliable compliance decisions where visibility was insufficient.

This approach is important for practical industrial AI adoption. Systems that overstate certainty may reduce operator trust, while systems that clearly handle uncertainty can support more reliable operational review.

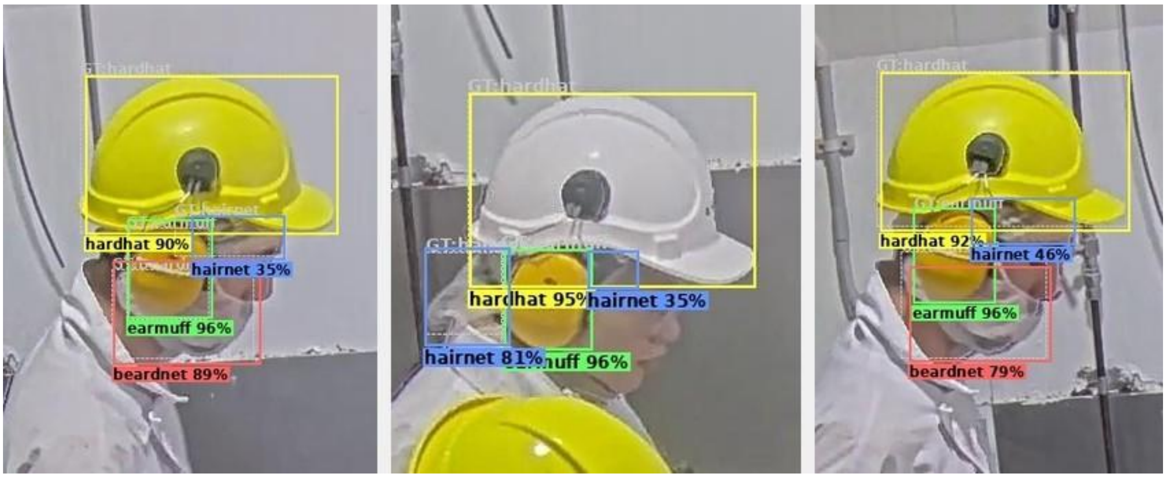

Figure 6.3.1: Example PPE detection results on anonymised head-region crops, showing simultaneous detection of multiple PPE indicators with associated confidence scores.

6.4 Boot Sanitisation Monitoring Results

The boot sanitisation component demonstrated the practical value of behavioural inference based on spatial presence and dwell-time analysis.

Rather than relying on detailed visual recognition of lower-body cleaning actions, the system assessed whether personnel interacted with sanitisation areas in a way consistent with expected operational procedures. This approach proved more suitable for visually constrained industrial environments where direct observation of detailed foot movement may be unreliable.

The results showed that zone- and time-based behavioural inference can provide meaningful compliance insight when combined with personnel tracking and session-level analysis.

This finding is significant for industry because it demonstrates that effective AI-assisted compliance monitoring does not always require complex action-recognition models. In some workflows, simpler and more robust behavioural indicators may provide greater practical reliability.

Figure 6.4.1 – Boot sanitisation compliance timing analysis. The SafePassAI interface calculates the duration each tracked individual remains within the configured boot-wash zone, enabling zone- and time-based compliance assessment linked to the person's tracking session.

6.5 Handwashing Behavioural Analysis Results

Handwashing analysis represented one of the most complex behavioural monitoring tasks within the project.

The system demonstrated the ability to analyse handwashing activity at a session level, considering duration, behavioural sequence, stage coverage, and overall hygiene-related indicators. This allowed the system to move beyond simple detection of presence at a handwashing station and toward assessment of how the behaviour was performed.

The project confirmed that frame-by-frame interpretation alone is not sufficient for reliable handwashing analysis. Temporary occlusion, hand movement, and natural variation in washing behaviour can create ambiguity. Session-level aggregation improved interpretability by considering behaviour over time.

The results also demonstrated the value of a progressive compliance approach. During early operational adoption, the system can retain detailed behavioural information while allowing compliance thresholds to be refined over time. This supports practical implementation without immediately imposing overly rigid automated enforcement.

6.6 Operational Reporting and Evidence Results

The project delivered structured reporting and review capabilities to make AI outputs usable for operational personnel.

The system was able to consolidate compliance-related information into session-level records. These records can support review of hygiene events, behavioural outcomes, and operational patterns.

The reporting capability is important because AI outputs alone are not sufficient for operational value. To be useful, analytical results must be presented in a way that supports decision-making, review, training, and process improvement.

The project demonstrated that AI-assisted monitoring can provide evidence-based visibility into compliance workflows. This may support future audit preparation, staff coaching, operational review, and continuous improvement activities.

6.7 Behavioural and Operational Impact

The project demonstrated early evidence that AI-assisted monitoring may influence operational behaviour by increasing awareness of hygiene and safety requirements.

Real-time feedback and compliance visibility can support behavioural reinforcement by making personnel more aware of required procedures during daily workflows.

This result is important because the value of the system is not limited to post-event reporting. AI-assisted monitoring may also act as an operational support mechanism that encourages improved compliance behaviour in real time.

The project also showed that successful adoption depends on usability and operator trust. AI systems must support existing workflows, provide understandable outputs, and allow human review where uncertainty or ambiguity exists.

6.8 Practical Reliability and Deployment Findings

The project demonstrated strong practical feasibility under real-world conditions. However, the results also showed that industrial AI deployment involves challenges that must be managed through system design and continuous refinement.

Key operational challenges included:

- personnel overlap,
- visual obstruction,
- variable movement patterns,
- constrained physical spaces,
- changing environmental conditions,
- and ambiguity in behavioural interpretation.

The project addressed these challenges through:

- multi-camera context,
- session-level aggregation,
- iterative refinement,
- uncertainty handling,
- and operational review workflows.

The results confirmed that practical AI deployment success depends on a complete system approach. Model accuracy is important, but it is only one part of the overall solution. Camera visibility, data quality, workflow integration, reporting design, and continuous refinement are equally important.

6.9 Summary of Key Results

The project achieved several important outcomes:

- demonstration of AI-assisted hygiene and safety compliance monitoring in a real industrial setting,
- development of a modular framework supporting multiple compliance workflows,
- validation of session-level behavioural interpretation as a practical method for compliance analysis,
- integration of monitoring outputs into operational review workflows,
- demonstration of evidence-based compliance reporting,
- and identification of future pathways for broader behavioural and operational monitoring applications.

Overall, the results show that AI-assisted behavioural compliance monitoring can provide practical value to the meat processing industry when designed around real operational conditions, user needs, and continuous improvement principles.

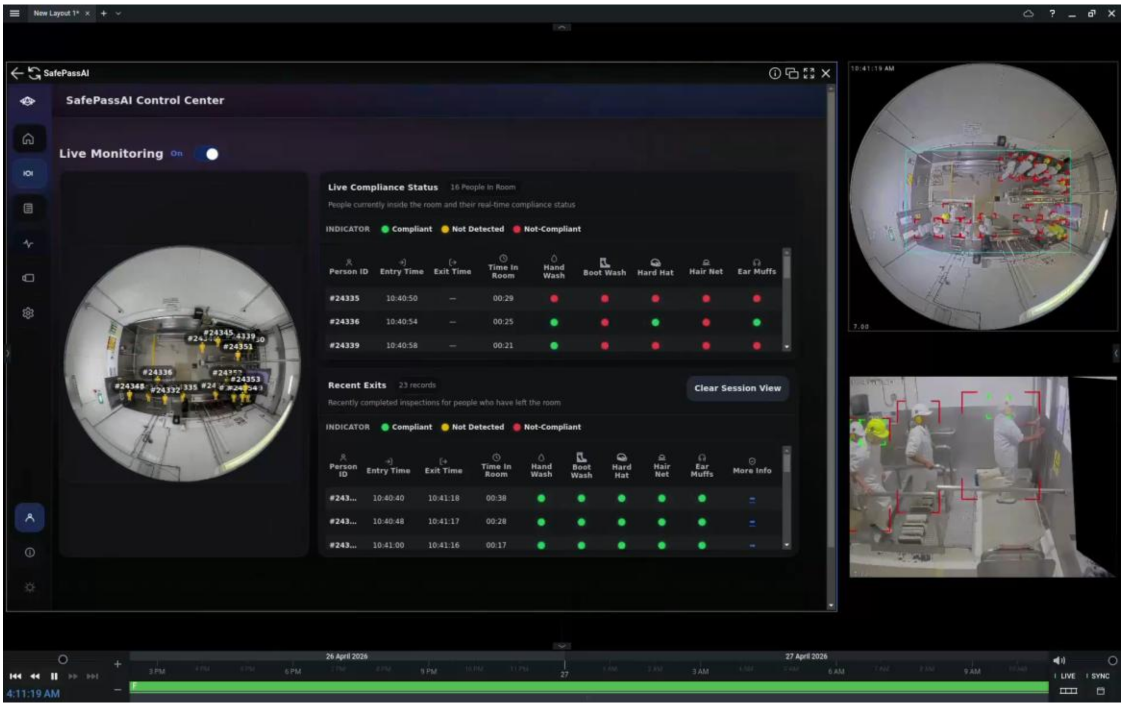

Figure 6.9.1 – SafePassAI live monitoring interface. The interface provides operational visibility of AI-assisted monitoring outputs and supports review of hygiene and safety compliance activity within a structured workflow..

7.0 Discussion

The SafePassAI project demonstrates the practical potential of AI-assisted behavioural compliance monitoring within meat processing environments. The project outcomes suggest that computer vision systems can provide value beyond simple detection tasks when they are designed around operational workflows, behavioural context, and reviewable reporting.

A central finding of the project is that successful industrial AI deployment requires a complete system approach. Model performance is important, but operational usefulness also depends on camera visibility, environmental conditions, tracking continuity, user interface design, evidence review, and the ability to refine the system over time.

7.1 Interpretation of Project Outcomes

The project demonstrated that AI-assisted monitoring can support hygiene and safety compliance workflows by providing structured visibility of personnel movement, PPE use, sanitation behaviour, and handwashing activity.

The key contribution of SafePassAI was not simply the development of individual AI models. Rather, the project showed how multiple analytical components can be integrated into a practical operational framework capable of supporting review, reporting, and continuous improvement.

This is an important distinction for industry adoption. A system that only detects objects may provide limited operational value. A system that combines detection with tracking, behavioural interpretation, session-level aggregation, and reporting can provide more meaningful insights into how compliance-related workflows are actually performed.

7.2 Practical Viability of Behavioural AI

The project confirmed that behavioural AI can be practically applied in industrial environments, but only when designed with real-world limitations in mind.

Processing facilities are not controlled laboratory settings. Personnel may move quickly, overlap with one another, interact with equipment, and perform procedures in slightly different ways. These conditions make highly detailed action recognition difficult.

SafePassAI addressed this by using behavioural inference and session-level interpretation rather than relying only on isolated frame-level detections. This approach allowed the system to interpret behaviour over time, reducing the impact of temporary ambiguity or incomplete visual observations.

The project therefore supports the view that practical behavioural AI systems should be designed around operational context, not just technical model capability.

7.3 Importance of Hybrid Architecture

The hybrid architecture used in the project provided an effective balance between edge-based processing and centralised analytics.

Edge-based processing supported efficient visual analysis close to the camera source, while centralised analytics allowed higher-level reasoning, behavioural aggregation, reporting, and system-wide interpretation.

This approach is relevant for industry because future deployments are likely to involve multiple cameras, multiple workflows, and increasing analytical complexity. A hybrid architecture provides a pathway for scaling these systems without placing all processing burden on either edge devices or central servers.

The project also showed that modular system design is important. Different analytical tasks can be improved or extended independently, allowing the platform to evolve over time as operational needs change.

7.4 Operational Adoption and Human Factors

The project highlighted that successful AI adoption depends on human and operational factors as much as technical performance.

For operational personnel to trust and use AI-assisted monitoring, outputs must be understandable, reviewable, and integrated into existing workflows. Systems that operate as unexplained black boxes are less likely to be accepted in real industrial settings.

SafePassAI was designed to support operational review rather than remove human oversight. This is particularly important in compliance environments, where context, judgement, and procedural knowledge remain valuable.

The project also demonstrated that feedback mechanisms and compliance visibility can support behavioural awareness. When personnel are aware that hygiene and safety workflows are being monitored and reinforced, this may contribute to improved procedure adherence.

7.5 Challenges and Limitations

The project identified several challenges that are likely to apply to many industrial AI deployments.

These include:

- visual obstruction and occlusion,
- personnel overlap,
- changing environmental conditions,
- variation in how individuals perform procedures,
- the need for representative training data,
- and the difficulty of interpreting behaviour from visual data alone.

The project showed that these challenges can be reduced, but not entirely eliminated, through careful system design. Multi-camera context, session-level aggregation, uncertainty handling, and iterative refinement all contributed to practical reliability.

Another important limitation is that AI systems require ongoing maintenance. Industrial environments change over time, and model performance may need to be improved through additional data collection, retraining, calibration, and workflow adjustment.

This reinforces the importance of treating AI-assisted monitoring as an evolving operational system rather than a one-off technology installation.

7.6 Industry Implications

The SafePassAI project has broader implications for the meat processing industry and other industrial sectors where procedural compliance is important.

The project demonstrates that existing video monitoring infrastructure can potentially be extended into intelligent operational support systems. Instead of using cameras only for passive observation or post-event review, AI-assisted systems can help generate structured insights about hygiene, safety, movement, and workflow behaviour.

This may support several industry outcomes, including:

- improved compliance visibility,
- more consistent review of operational procedures,
- better support for staff training,
- improved audit readiness,
- and data-informed process improvement.

The project also suggests that behavioural AI may be applicable beyond hygiene monitoring. Similar methodologies could be adapted for safety procedure verification, workflow analysis, congestion monitoring, operational performance assessment, and other compliance-related tasks.

7.7 Future Research and Development Direction

The project established a foundation for future research and development in industrial behavioural AI.

Future work should focus on improving behavioural model robustness, expanding datasets, refining tracking and session association methods, and validating the approach across additional operational environments.

Another important future direction is privacy-conscious identity association. The current approach focuses on tracking and session association rather than direct personal recognition. Future systems may explore appropriate identity-linking methods where operationally justified and governed by clear privacy, consultation, and compliance frameworks.

The project also supports future expansion toward broader operational intelligence. The same principles used for hygiene and safety monitoring could potentially be extended to other workflows where understanding behaviour over time is valuable.

Overall, SafePassAI demonstrates a pathway for moving from passive video monitoring toward intelligent, evidence-based, and operationally integrated compliance support systems.

8.0 Conclusions

The SafePassAI project successfully demonstrated that AI-assisted computer vision can support hygiene and safety compliance monitoring within meat processing environments.

The project developed and validated a modular behavioural monitoring framework capable of supporting personnel localisation, PPE monitoring, boot sanitisation assessment, handwashing analysis, operational reporting, and evidence-based review.

A key conclusion is that practical compliance monitoring requires more than isolated AI detections. The project showed that meaningful operational insight is achieved when visual observations are combined with tracking, behavioural interpretation, session-level aggregation, reporting, and human review.

The project also demonstrated that behavioural AI can operate practically in complex industrial environments when designed around real-world constraints. These constraints include visual obstruction, personnel overlap, changing environmental conditions, and variation in how procedures are performed.

The hybrid architecture developed through the project provided a practical balance between edge-based processing and centralised analytics. This approach supported scalability, modularity, and the ability to interpret behaviour across operational workflows.

The project confirmed that AI-assisted monitoring has potential to improve hygiene and safety compliance visibility, reduce reliance on fully manual observation, support operational review, and provide structured evidence for training, audit, and process improvement.

Overall, SafePassAI provides a practical foundation for future intelligent monitoring systems within the meat processing industry and demonstrates how AI can help transform video monitoring from passive observation into operational decision support.

9.0 Recommendations

Based on the outcomes of the SafePassAI project, several recommendations are proposed for future research, development, and industry adoption of AI-assisted hygiene and safety compliance monitoring systems.

9.1 Continued Dataset Expansion and Behavioural Model Refinement

Future work should continue expanding datasets using representative operational examples. Industrial environments vary across facilities, shifts, lighting conditions, workflows, equipment layouts, and personnel behaviour. Broader datasets will improve model robustness and support more reliable performance across different operational conditions.

Ongoing model refinement should focus on difficult real-world scenarios, including visual obstruction, personnel overlap, ambiguous behaviours, and procedure variations.

9.2 Strengthen Behavioural Interpretation Methods

Further research should continue improving behavioural interpretation methods, particularly for workflows that require assessment over time rather than single-frame detection.

Session-level aggregation, time-based analysis, and contextual interpretation should remain key design principles. These methods are especially important for hygiene and safety procedures where compliance depends on a sequence of actions or interaction with specific operational areas.

9.3 Improve Multi-Camera Tracking and Session Association

Future development should continue improving multi-camera tracking, session association, and identity continuity methods. Reliable association of compliance events with operational sessions is essential for meaningful reporting and review.

Future systems should also explore privacy-conscious identity association methods where appropriate. Any identity-linked capability should be governed by clear consultation, privacy, and operational policies.

9.4 Expand Human-in-the-Loop Review Workflows

AI-assisted compliance monitoring should continue to support human review and operational feedback. Future systems should allow operators or authorised personnel to flag uncertain, incorrect, or ambiguous outputs for review.

This type of feedback loop can support model refinement, improve trust, identify edge cases, and help ensure the system remains aligned with real operational conditions.

9.5 Support Progressive Operational Adoption

Future deployments should use a progressive adoption approach. Rather than immediately applying strict automated enforcement, systems should initially support visibility, review, training, and operational learning.

Compliance thresholds and reporting settings should be configurable so that facilities can align the system with their procedures, maturity level, and operational requirements.

9.6 Validate Across Additional Facilities

Further validation across additional processing environments is recommended. This would help determine how well the methodology generalises across different facility layouts, workflows, camera positions, workforce patterns, and hygiene procedures.

Broader validation would also support development of industry-level guidance for AI-assisted compliance monitoring.

9.7 Explore Broader Industrial Applications

The SafePassAI methodology may be extended beyond hygiene monitoring. Future research could investigate applications such as safety procedure verification, workflow analysis, congestion monitoring, operational performance assessment, and broader procedural compliance monitoring.

This would help determine the wider value of behavioural AI as an operational intelligence tool for the meat processing industry and related sectors.

10.0 Project outputs

The SafePassAI project delivered a range of technical, operational, and methodological outputs relevant to AI-assisted hygiene and safety compliance monitoring.

10.1 Technical Outputs

The project developed a modular AI-assisted monitoring framework capable of supporting multiple compliance workflows. Key technical outputs included:

- personnel localisation and tracking capability,
- PPE monitoring capability,
- boot sanitisation assessment methodology,
- handwashing behavioural analysis methodology,
- session-level behavioural aggregation,
- operational reporting workflows,
- and a hybrid AI system architecture.

10.2 Operational Outputs

The project demonstrated the practical application of AI-assisted monitoring under real-world industrial conditions. Operational outputs included:

- validation of compliance monitoring workflows in an industrial environment,
- demonstration of multi-module AI-assisted monitoring,
- reviewable compliance records,
- evidence-based operational review workflows,
- and practical learnings relating to deployment, usability, and refinement.

10.3 Research and Methodological Outputs

The project generated several research and methodological outputs that may inform future industry development, including:

- a behavioural AI methodology for compliance monitoring,
- a session-based approach to interpreting hygiene and safety behaviours,
- practical learnings on applying computer vision in visually constrained environments,
- evidence that hybrid edge/server architectures can support industrial AI deployment,
- and guidance for future refinement, adoption, and expansion of AI-assisted monitoring systems.

10.4 Industry Value Outputs

The project provides value to industry by demonstrating a pathway for improving compliance visibility, supporting operational review, and reducing reliance on fully manual monitoring.

- The outcomes may support future industry activities relating to:
- hygiene and safety compliance improvement,
- staff training and feedback,
- audit preparation,
- operational process review,
- and broader intelligent monitoring adoption.

Overall, the project outputs provide a foundation for future AI-assisted compliance and operational intelligence systems in meat processing environments.

11.0 Bibliography

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