Camera-based Intruder Detection and Monitoring of Ship Crew Work Hours

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Abstract

Due to technological developments and commercial pressures, the crew size on ships has gradually decreased. As a result of the decrease in crew sizes as well as port and turnaround times, seafarers' work hours have increased and working on ships has become increasingly challenging. The health and performance of fatigued crews deteriorates and the risk of causing accidents increases. The working hour limits of seafarers are specified in international legislation, but there is no system that provides evidence to check whether the records of work and rest hours reflect the truth. In this study, a face recognition system is presented using CCTV cameras on ships to monitor the work and rest hours of the crew, and to detect intruders on ships. A new CCTV dataset from a commercial ship is presented to study intruder detection and work hours monitoring.

1. Introduction

Maritime transportation, which is the dominant medium for international trade, is carried out by approximately 2 million seafarers worldwide who work day and night. Due to technological advances and commercial pressure, the number of crews on ships has gradually decreased. As a result of the decrease in crew sizes as well as port and turnaround times, seafarers' work hours have increased and working on ships has become increasingly demanding [7, 8, 11, 19, 21, 23]. Seafarers work an average of 74.9 hours per week, significantly higher than the global average of 43 hours per week identified by the International Labour Organization (ILO) 2018 General Survey [6]. Other difficulties specific to working on a ship also increase fatigue.

Fatigue is a major threat to ship safety as well as seafarers' occupational safety and health. It impairs seafarers' performance and has long-term negative effects on health [17]. Fatigue results in decreased alertness, mental concentration, cognitive processing speed and motivation, decreased attention and increased reaction time [15, 18]. For these reasons, it is of great importance to effectively control whether the duration of seafarers' employment in practice complies with international regulations. Seafarer work and rest hours are regulated in the Seafarers' Training, Certification and Watchkeeping Code of the International Convention on Standards of Training, Certification, and Watchkeeping for Seafarers (STCW) and the Maritime Labor Convention (MLC), 2006. Current maritime regulations permit workweeks of up to 91 or even 98 hours [4]. The regulations of the United Nations International Maritime Organization (IMO) establish mandatory rest intervals of at least 10 hours in any 24-hour period and 77 hours in any 7-day period; the rest period may be divided into a maximum of two parts of at least 6 hours each. There shall be no more than 14 hours between any two consecutive periods. Maximum working hours shall not exceed 14 hours in any 24-hour period and 72 hours in any seven-day period [16]. However, the ship's master may make an exception, particularly in an emergency, to ensure the safety of the ship. Working in such a demanding and safety-critical work environment for such long periods of time, fatigue of seafarers is a much bigger problem than in many other sectors. Therefore, strict control of the working hours of the members is essential.

Checking whether working and rest hours on ships are implemented in accordance with the regulations is carried out by the Flag State and Port State Control inspectors

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as well as the company superintendent, based entirely on forms consisting of the crew's own declarations. Inspectors use methods to verify the accuracy of working and rest hour records on ships such as cross-referencing records, observation of crew's physical condition and interviewing crew. Because records are kept entirely based on crew statements, it is very difficult to detect evidence of non-compliance. This hinders effective monitoring and creates the risk of records being adjusted. Inspectors face significant challenges in verifying records. In a survey conducted among Port State Control Officers, 80% of the respondents stated that it is not easy to detect adjustments in work/rest hour records. Converting detected discrepancies into irrefutable evidence poses another challenge. Inspectors' own subjective perceptions and intuitions alone are not sufficient grounds for objective verification of fatigue. On the other hand, it is difficult to take action because STCW states that captains can deviate from rest hours in certain circumstances and they can use it as an excuse [4].

A significant 88.3% of seafarers admit to exceeding work/rest hour limits at least once a month. Alarmingly, 16.5% exceed the limits more than ten times a month [5]. However, of the 10,812 deficiencies identified by the United States Coast Guard between 2018 and 2020, only 3 were related to working and rest hours. Although work and rest hours non-compliance is so common on ships, the fact that the number of deficiencies due to work and rest hours in worldwide Port State Control (PSC) inspections is very low indicates that work and rest hours non-compliance is not adequately detected during Port State Control inspections. On the other hand, the priorities in PSC inspections appear to be technical issues on board, not seafarer issues, which contrasts with the fact that the human element contributes to most accidents [4].

1.1. Motivation and Proposed Approach

Considering the limitations of existing record-keeping methods, there is an obvious need of changing the monitoring systems. As already noted in the literature, a secure solution has not yet been identified, and surveyors should not exclusively rely on paperwork and other forms of data collection should be promoted. Some recommend magnetic cards or intelligent wrist watch on ships as an alternative solution to manual inputs [4]. However, it will still be possible to fool the system since magnetic cards or intelligent wrist watches can be used instead of others in this method.

Contributions: None of the previous studies were able to present a system that can detect whether work and rest hours records reflect the truth with evidence and warn stakeholders before non-compliance occur. To fill this gap, this study

- proposes using CCTV cameras and face recognition algorithms on ships to track the time personnel spend at their posts, thus automatically detecting whether working hour limits are exceeded in a proven manner;
- demonstrates another important application of face recognition, detecting unknown people (intruders) on ships;
- introduces a new dataset that comprises CCTV recordings from a commercial ship to train and test the proposed methods.

CCTV cameras are becoming a standard technology on ships. Recently, the U.S. Coast Guard has required vessels over 500 gross tonnage to install video and audio surveillance systems capable of continuous and uninterrupted recording no later than December 23, 2024, or the next scheduled dry-docking date [1].

The proposed method provides a practical means for Port State Control, Flag State Control, Class Inspector, and company inspectors to check the reports since they would not be able to manually inspect ship cameras and detect whether working hours are exceeded in a time-efficient manner. Furthermore, the proposed face recognition system can serve as an intruder detection system as it can timely detect unknown people and alert the security personnel.

Another motivation for the proposed method is to prevent unintentional errors that are common due to retrospectively entering work hours. Ideally, crew members should keep their own working hours records daily, but this is difficult during busy days. The current recording practice tends to increase the administrative workload of the crew, especially when the record is allowed to accumulate until the end of a week or month. In this way, it is often seen that records are filled in retrospectively and that records are erroneous due to incorrect recall. However, with the automatic work hours detection from camera recordings, the crew's working hours can be automatically determined and recorded. Automated calculation of work hours from CCTV recordings can also prevent disputes about overtime wage crew members receive when they work extra hours.

In the current system, unless any crew member whistleblows, non-compliance cannot be effectively detected. However, as suggested in this study; if working hours are monitored through cameras, the fatigue problem can be prevented in a sustainable way without causing hostility between the crew and the company. Thus, ships will be operated more fairly and more safely.

Privacy is one of the most critical issues associated with the use of CCTV cameras and face recognition. Continuous surveillance can create a sense of intrusion, particularly if cameras are installed in areas designated for rest or recreation. To address these concerns, it is essential to limit the scope of CCTV monitoring to operational areas such as the bridge, engine room, and other workspaces. Rest quarters and private spaces should be explicitly excluded from monitoring, and policies should clearly articulate the purpose and boundaries of surveillance. Transparency is key to mitigating privacy concerns. Crew members must be informed about the objectives of CCTV implementation, including its focus on safety and compliance rather than punitive enforcement. Clear communication fosters trust and ensures that surveillance is perceived as a supportive tool rather than an intrusive measure.

1.2. Related Work

The proposed system for detecting intruders and estimating working hours based on face recognition leverages the advancements in face recognition and its practical applications. Most of the state-of-the-art face recognition modes are trained on large-scale datasets, which contain millions of images mostly taken from the Internet [3]. However, these datasets are mostly biased and pose some ethical concerns. Recent research has shifted its focus from real-face data to synthetic datasets to address these challenges. A large-scale synthetic dataset is provided in [3], while it shows that the data augmentation technique can significantly reduce the gap between the real data and synthetic data. Similarly, a large-scale synthetic dataset is also generated using a diffusion model based on a dual condition face generator in [13]. In addition to the large number of synthetic datasets, a large number of unlabelled face datasets are available. To explore the potential of these unlabelled face datasets, a self-supervised pretraining approach is proposed to facilitate the transfer of generalized face recognition capabilities in [22]. In addition to supervised face recognition, an unsupervised person re-identification system utilizing the aerial image is proposed in [12].

Face recognition has been applied to diverse applications, such as estimating the number of occupants [9] and ensuring workplace safety [10]. In [9], a deep learning model is proposed to estimate the number of people in a large area using multiple cameras. Despite the vast applications of face recognition across various domains, the number of applications in the maritime sector is still minimal. A real-time crew safety detection and early warning system is proposed in [14]. The system gives a warning if the crew does not wear safety ropes inside the working area.

In this work, we propose a crew-tracking method for intruder detection and working hour estimation. We also provide a real CCTV dataset that shows the activity of crews in different areas of the ship. We train a face recognition model using the real faces of the crew members.

2. Methodology

In this section, we propose a crew tracking method based on face detection and recognition to estimate the working hours and to detect intruders on the ship. By leveraging a face recognition model, we identify the person in the video and their respective appearance timestamps, which are the basis for estimating their working hours. In addition, the recognition scores generated by the face recognition module enable the identification of potential intruders on the ship. In the subsequent sections, we describe the face detection model, face recognition model, intruder detection, and working hour estimation method.

2.1. Face Detection Model

Our proposed method begins by detecting the faces from the videos. To detect the face, we employ the pretrained YuNet, a lightweight and efficient deep-learning-based model integrated within the OpenCV library [24]. The model provides the bounding box enclosing the face with a confidence score. As the resolution of typical CCTV video might be low, a high confidence score can effectively filters out the non-face images. In our experiments, presented in the next section, we use a confidence score of 0.8 to detect the final faces.

The face detection model performs two primary objectives in our workflow. First, it is employed to generate a dataset of crew members' face images, which is subsequently used to train the face recognition model. Second, after training, the face detection model operates along with the trained face recognition model in test to identify individual crew members within the videos.

2.2. Face Recognition Model

To recognize the crew on the ship, we extract the Local Binary Patterns (LBP) features from [2] because of its simplicity and efficiency [2]. Before passing a face image through the face recognition model, we pre-process it by converting from RGB to Grayscale, resizing, and histogram equalization. The pre-processing steps enhance the contrast of the image and ensure the images are of equal size.

The face recognition model processes the pre-processed image and extracts the feature vector using the LBP histogram. To classify an input face image, it calculates the Euclidean distance between the feature vector of the input image and the training images. Then, the nearest neighbor classifier is used to determine the nearest class for the input face image. The face recognition model can be described as,

$$\boldsymbol{X}_p = Preprocessing(\boldsymbol{X}_d) \tag{1}$$

$$(c, d) = FaceRecognizer(\boldsymbol{X}_p) \tag{2}$$

where, $\boldsymbol{X}_d$ is the detected image and $\boldsymbol{X}_p \in \mathbb{R}^{100\times100}$ is the grayscale pre-processed image with both height and width equal to 100. The variable c represents the predicted class, and d is the minimum distance between the pre-processed image $\boldsymbol{X}_p$ and the training images.

2.3. Intruder Detection

In addition to face recognition, our model also detects intruders, which is essential for ensuring security, especially when the ship is in the port area.

The face recognition model derives the Euclidean distance between the LBP histograms of the input image and the training images, as shown in Eq. (2). The class with the smallest distance is identified as the predicted class. The distance will be minimal for images corresponding to one of the known classes, whereas the distance is expected to be higher for an intruder. A larger distance reflects more dissimilarity between the input and the training images. Leveraging this characteristic, the proposed method effectively identifies intruders. If the computed distance surpasses a predefined threshold h, the individual in the image is classified as an intruder. The threshold h is calculated by the following equation,

$$h = \max_{i \in \{1,\ldots,N\}} \left(\mu_i + \alpha \cdot \sigma_i\right), \quad (3)$$

where N is the number of known classes, μ_i and σ_i are the mean and standard deviation of the distance score d, respectively, for the rightly predicted person from class i of the validation dataset. The variable α is a hyperparameter that regulates the threshold h. For the experiments in the next section, we selected the optimal value of $\alpha = 1$ from the set $0, 1, 1.5$.

2.4. Work Hours Estimation

Estimating the crew members' work hours is essential to automatically determining excessive or insufficient working hours. This process employs face detection and recognition models to monitor individual crew members. When a crew member is identified, we log their appearance with a timestamp. By continuously monitoring the crew members over a period of time, we generate a timeline that contains the crew member IDs and their corresponding appearance timestamps. By analyzing the timeline data, we extract the members' hourly presence information, which is used to calculate the working hours. To achieve this, we count the presence of a crew member in each hour. If the presence value in an hour is greater than or equal to a threshold value, it is considered an hourly presence for that crew member.

3. Experiments

To demonstrate the proposed methods, we use a CCTV dataset from a ship under written permission from the company and crew members who appear in the recordings. We also consulted with the Institutional Review Board (IRB) in our institution and got the written response that no IRB approval is needed since this study does not interact with the recorded people.

Crew ID	Num. of Images
1	226
2	502
3	431
4	66
5	70
6	3
7	75
8	5
9	7
10	40
11	14
12	63
13	5
14	3
15	7
16	32
17	7
18	3
19	128
20	12
21	33
22	52
23	5
24	3
25	9
26	20
Total	1821

Table 1. Crew IDs and the corresponding number of face images in the face image dataset derived by cropping the faces from the videos using the face detector.

3.1. Dataset

The video recordings of 26 CCTV cameras on an IMO Type II Chemical and Oil Tanker with a capacity of 10,740 dead weight tons were examined between 11 August 2024 and 01 December 2024. The dataset consists of a total of 101,376 videos, each less than 7 seconds long. The total size of the data is 1 TB. [1]

There are 3, 4, 7, 6 and 6 CCTV cameras on the navigation bridge deck, poop deck, 2nd deck, upper platform deck (1st deck) and lower platform deck, respectively. The locations of these cameras on different decks are shown in Fig. 1. In addition, sample frames from different videos are presented in Fig. 2. The video quality is not high, making the face detection and recognition challenging, which

[1] The dataset and code are publicly available in: https://github.com/Secure-and-Intelligent-Systems-Lab/Intruder_Detection_and_Work_Hour_Estimation

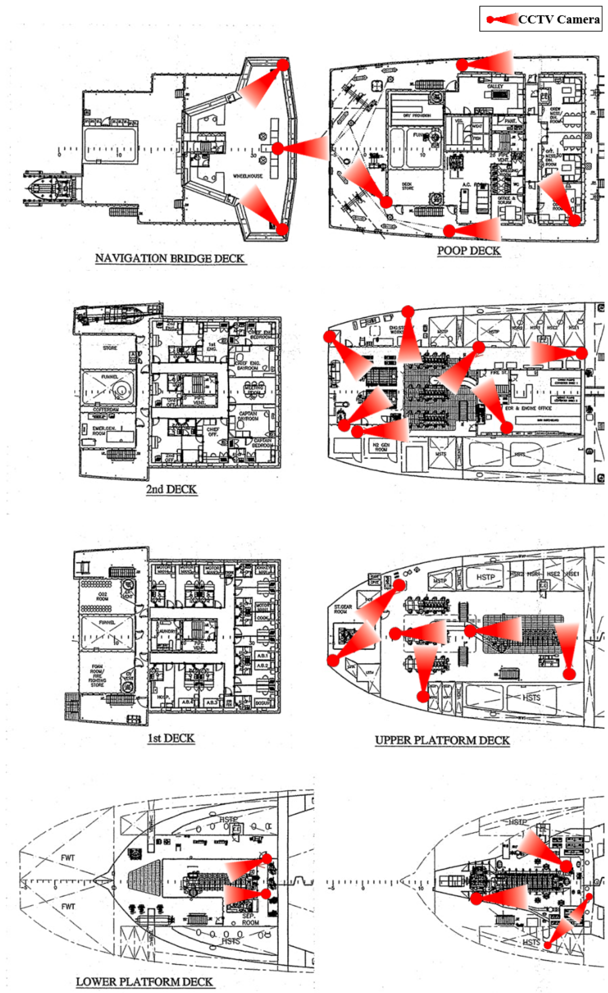

Figure 1. Locations of 26 CCTV cameras on the decks are shown.

Crew ID	Precision	Recall	F1-score	Accuracy
1	0.92	0.98	0.95	0.94
2	0.97	0.97	0.97	
3	0.91	0.90	0.90	
4	0.92	0.86	0.89	
5	0.93	1.00	0.97	
7	1.00	0.93	0.97	
12	0.86	0.92	0.89	
19	0.92	0.85	0.88	
22	1.00	1.00	1.00	

Table 2. Performance of the face recognition model without intruders in the test dataset.

would be the case in practice with legacy CCTV cameras present in many ships worldwide.

Crew ID	Precision	Recall	F1-score	Accuracy
1	0.98	0.93	0.96	0.90
2	0.98	0.89	0.93	
3	0.93	0.78	0.85	
4	0.92	0.79	0.85	
5	1.00	0.93	0.96	
7	1.00	0.93	0.97	
12	0.92	0.85	0.88	
19	1.00	0.73	0.84	
22	0.92	1.00	0.96	
Intruder	0.82	0.97	0.89	

Table 3. Performance of the face recognition model after adding the Intruder class in the test dataset. The face recognition model identifies crew members based on the training classes, and intruders are subsequently detected using the distance scores.

3.2. Results

The crew member face image dataset contains the face images of 26 crew members. Tab. 1 depicts the distribution of face images for each crew member. To train the face recognition model, we selected the top 9 crew members with the highest number of face images because the number of face images for each remaining crew member is very low. To train and evaluate the face recognition model, we split the images of the selected crew members into training, validation, and test datasets in a 3:1:1 ratio. Fig. 4 illustrates the confusion matrix for the predicted classes on the test dataset, demonstrating the model's effectiveness in identifying each individual. In addition, Tab. 2 presents the model's precision, recall, F1-score, and overall accuracy. Despite the low resolution of CCTV recordings in the dataset, the face recognition performance is very good, indicating a promising applicability in real-world applications. With the higher resolution recordings of state-of-the-art cameras, face recognition results are expected to be even better.

To evaluate the performance of the intruder detection method, we introduce an intruder class to the test dataset. The intruder class comprises all crew members' face images except the previously selected nine crew members. After predicting the class for a detected face in the new test dataset using the trained face recognition model, we decide there is an intruder by comparing the distance score d, given in Eq. (2), with the threshold h, given in Eq. (3). The confusion matrix is presented in Fig. 5, which shows that our model successfully detects the intruders. However, some normal crew members are mistakenly classified as intruders, which can be attributed to the low video quality. The overall accuracy, precision, recall, and F1-score of the intruder detection method is shown in Tab. 3.

In addition to the intruder detection, we demonstrate our

Figure 2. Sample frames from the videos, illustrating the diversity in the video dataset.

idea of work hour estimation presented in Sec. 2.4. Figure 3 illustrates the hourly presence of crew members 1 and 12 over a 48-hour period. During these 48 hours, they were detected on the cameras in 5 and 10 hours, respectively, which can be used to estimate their working hours. Alternatively, considering a binary rest-work pattern and the gaps in the coverage of cameras (i.e., crew may be working in areas with no camera), a threshold can be applied to connect intermittent appearances. For example, assuming a person is continuously working if they are detected again within 6 hours, the working hours of crew members 1 and 12 are estimated as 8 and 14, respectively.

4. Limitations

The proposed tracking method does not take into account the camera locations. The results can be improved in a future work by considering the proximity of camera locations. For instance, if person A is seen walking by a camera, there is a higher probability that the same person will soon be seen on other nearby cameras. Building tracking models which consider camera locations can significantly lower false detections.

In a survey conducted in 2017, 85% of the crew stated that they spend all their free time in their cabins. Very few indicated that they spend their free time engaged in com-

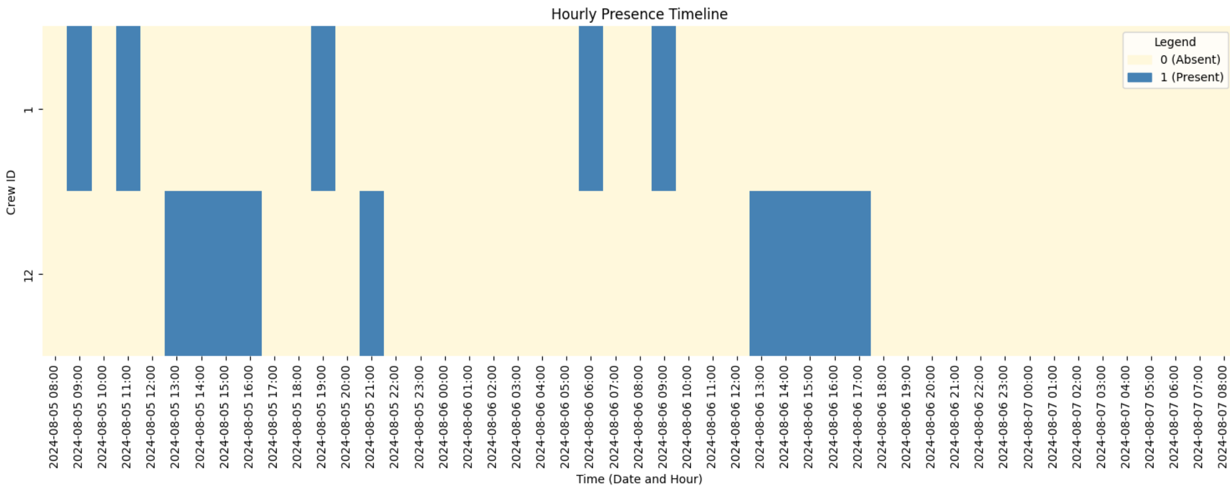

Figure 3. Hourly presence timeline for crew members 1 and 12 is presented over 48 hours. If a person is observed during a one-hour period, that particular hour in the timeline is marked by green.

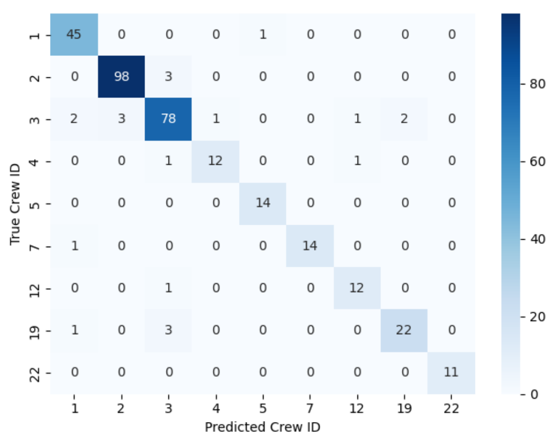

Figure 4. Confusion matrix without intruder in the test dataset

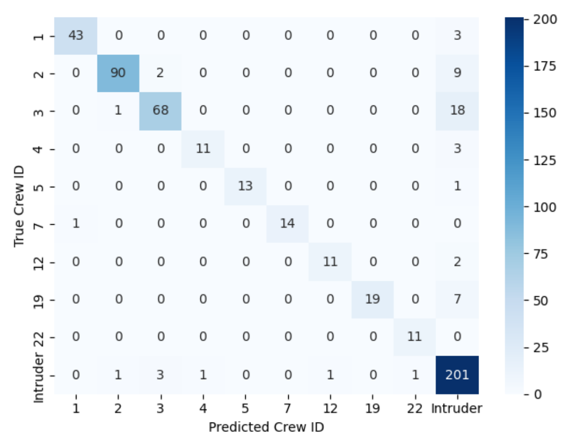

Figure 5. Confusion matrix with intruder in the test dataset

munal activities such as watching TV/DVD together (5%), chatting with colleagues (3%), singing with others (2%) and work out (3%) [20]. Therefore, we assumed that the crew are working almost all the time they are seen on the ship's cameras. On the other hand, since there are no cameras inside the cabins of the ship's personnel, it is not possible to determine whether the personnel in the cabin are really resting. It is also possible for the personnel to do some of the possible work related to the ship in their cabin. In addition, although the personnel are given sufficient rest hours, there is also the possibility that the personnel may increase their fatigue level by engaging in activities that will tire them instead of resting on their own.

5. Conclusion and Future Studies

In maritime transportation, non-compliance with the work-hour rule and the resulting fatigue will decrease if the control of working and rest hours can be done in a proven manner. When fatigue decreases, accidents and therefore damage to life, property and the environment will also decrease. The performance of the crew working in more humane conditions will increase, and the rate of leaving the profession will decrease.

Studies on seafarers in the maritime sector are currently ongoing. The Maritime Labour Convention (MLC) was amended in 2022 to enter into force on 23 December 2024. The automatic working hour monitoring system presented in this study also contributes to the achievement of the 6th Strategic Direction (SD) article titled "Address the human element" in the current Strategic Plan published by IMO for the years 2024-2029. The proposed system provides the opportunity to check work and rest hours compliance with evidence and accelerates the control processes carried out by Port State authorities such as the United States Coast Guard.

CCTV systems along with machine learning algorithms represent a transformative approach to addressing several important problems in maritime transportation, including intruder detection and the persistent issue of resting hour compliance. By providing real-time monitoring, objective data collection, and actionable insights, these systems enhance safety, accountability, and operational efficiency. However, their successful implementation requires careful consideration of ethical, technical, and operational challenges. Through transparent policies respecting privacy and effective training, CCTV camera technologies can become a cornerstone of modern maritime safety and compliance.

Integrating CCTV systems with fatigue detection technologies enhances safety further. AI algorithms can process visual cues such as irregular movements, slouching, or prolonged inactivity, which are often indicative of fatigue. These alerts can prompt supervisors to rotate shifts, ensure rest breaks, or even mandate longer rest periods, depending on the severity of the observed behavior.

This study aims to provide a framework to determine whether the personnel on cargo ships are working in accordance with the rest hours rules, but it is also possible to determine whether the crew working on sea vessels such as fishing boats and yachts, where the STCW Work and Rest Hours rules are not applied, are working in accordance with the rest hours rules with the framework presented in this study. Moreover, since most of these sea vessels are much smaller than cargo ships and can be more easily monitored with much fewer cameras, it is easier to apply the framework presented in this study.

The system presented in this study can be applied not only on ships but also in many other places such as workplaces where there is a risk of critical accidents due to personnel fatigue.

By ensuring that the insurance and Protection and Indemnity Club premiums of ships equipped with CCTV cameras that recognize human faces and automatically detect resting hours are kept lower, it can be made financially profitable for ship operators to bear the costs required to install such cameras.

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