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AI-Powered Video Analysis for Objective Maritime Skills Evaluation and Performance Enhancement

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ABSTRACT

Maritime practical skills assessment relies on instructor subjective observation prone to 30-40% inter-rater reliability variance, creating fairness concerns and limiting detailed performance analytics essential for competency-based training. This research presents the design and validation of computer vision systems analyzing video recordings of maritime practical assessments to automatically evaluate student performance against STCW competency rubrics, identify safety violations, assess teamwork dynamics, and provide objective scoring reducing instructor subjectivity bias. Employing design science research methodology with qualitative stakeholder evaluation, the study engaged maritime skills instructors (n=14), assessment coordinators (n=6), and students (n=18) through structured interviews examining evaluation accuracy, fairness perceptions, and feedback utility. Deep learning computer vision models incorporating pose estimation, object detection, action recognition, and multi-person tracking achieved 82% agreement with expert human evaluators while generating detailed performance analytics impossible through manual observation including spatial positioning accuracy, procedure timing analysis, and team coordination metrics. Thematic analysis revealed strong support for AI-assisted assessment, identifying critical themes of evaluation objectivity, performance feedback detail, and instructor workload reduction. Pilot implementation with 340 practical assessments across mooring operations, firefighting, lifeboat drills, and bridge communication exercises demonstrated 91% student satisfaction with detailed feedback, 68% reduction in assessment administration time, and 89% standardized evaluation consistency, contributing validated computer vision architectures and empirical evidence supporting intelligent assessment automation in maritime vocational training contexts addressing subjectivity challenges and scalability constraints.

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1. Introduction

Practical skills assessment represents the cornerstone of competency-based maritime education, with International Maritime Organization STCW Convention mandating comprehensive demonstration of physical competencies spanning vessel operations, safety procedures, emergency response, and teamwork coordination that cannot be evaluated through written examinations alone, yet current assessment methodologies relying primarily on instructor subjective observation suffer from multiple critical limitations including inter-rater reliability variance averaging 30-40% across different evaluators assessing identical performance creating fairness concerns and grade appeals, limited performance analytics as human observers can track only gross competency achievement versus detailed execution quality metrics, assessment scalability constraints as intensive instructor attention requirements limit throughput when multiple students require simultaneous evaluation, delayed feedback delivery as instructors manually compile observation notes and scoring rubrics hours or days after practical exercises reducing learning effectiveness, and quality assurance difficulties as lack of permanent performance records prevents systematic review of assessment validity or instructor calibration training [1].

These assessment limitations prove particularly problematic in maritime training where safety-critical competencies including emergency response, confined space operations, and vessel maneuvering demand precise execution standards difficult to evaluate consistently through subjective human judgment susceptible to fatigue effects, recency bias, halo effects, and evaluator expertise variations [2]. Sekolah Tinggi Ilmu Pelayaran Jakarta, Indonesia's flagship maritime academy, conducts approximately 15,000 practical skills assessments annually across diverse competency domains including mooring and anchoring operations, firefighting and damage control, lifeboat launching and survival craft operations, bridge team communication and navigation watch procedures, engine room maintenance and troubleshooting, cargo handling and stowage, and medical emergency response, requiring substantial instructor resources as typical assessment sessions involve 2-3 evaluators observing 6-8 students performing complex procedures over 45-90 minute periods, with evaluators simultaneously tracking individual performance against multi-dimensional rubrics while ensuring safety compliance and managing operational logistics [3].

Current assessment workflows generate documented challenges including inter-rater disagreements requiring third-party arbitration in 12-15% of evaluations, limited performance feedback beyond holistic competency scores as time-constrained instructors cannot provide detailed execution analysis for each student, assessment bottlenecks during peak examination periods when simulator and practical facility capacity cannot accommodate all students requiring evaluation, and institutional quality assurance concerns as Port State Control inspections increasingly scrutinize assessment rigor and documentation adequacy demanding evidence of objective, standardized evaluation methodologies [4]. The fundamental research problem addresses the absence of automated, objective assessment technologies capable of analyzing complex maritime practical skills performance with accuracy approaching or exceeding human expert evaluation while generating detailed performance analytics, ensuring consistent scoring across evaluators and time periods, scaling to institutional assessment volumes, and providing immediate detailed feedback supporting student learning, all implemented within resource constraints limiting expensive specialized equipment procurement and technical support capacity.

Specifically, this research investigates four interconnected questions: What computer vision architectures and deep learning models effectively analyze video recordings of maritime practical assessments to automatically evaluate student performance across diverse competency domains including mooring operations, firefighting, lifeboat drills, and bridge communication? How accurately can AI-powered assessment systems detect safety violations, identify procedural errors, measure teamwork coordination, and evaluate performance quality compared to expert human evaluators serving as gold-standard benchmarks? What performance analytics capabilities beyond human observer limitations provide actionable feedback for student learning improvement, instructor training enhancement, and institutional curriculum development? How do computer vision assessment systems impact evaluation fairness perceptions, student satisfaction with feedback, instructor workload efficiency, and institutional quality assurance when implemented in Indonesian maritime training contexts characterized by diverse practical facilities and limited technical infrastructure?

This research contributes significant theoretical and practical advances to computer vision educational applications and maritime training assessment scholarship while addressing critical gaps in automated skills evaluation literature. Theoretically, it extends computer vision frameworks predominantly developed for sports performance analysis, manufacturing quality control, or simple gesture recognition into complex multi-person maritime procedural assessment requiring simultaneous tracking of multiple students, equipment interactions, spatial positioning, temporal sequencing, teamwork coordination, and safety compliance across diverse operational environments. Methodologically, it validates deep learning approaches balancing automated assessment efficiency with instructor oversight and interpretability requirements, avoiding both extremes of purely subjective manual evaluation or completely autonomous AI scoring lacking human judgment integration.

Practically, the research delivers immediately deployable computer vision systems supporting Indonesia's maritime education quality assurance imperatives while providing empirical evidence of AI assessment's impact on evaluation consistency, student learning, and institutional efficiency. The investigation employs mixed-methods design science methodology combining iterative computer vision development with comprehensive qualitative stakeholder evaluation through maritime skills instructor interviews (n=14 representing mooring, firefighting, lifeboat, bridge operations, and engine room assessments), assessment coordinator consultations (n=6 managing institutional evaluation quality assurance), and student focus groups (n=18 experiencing AI-assessed practical exercises), analyzing perspectives through systematic thematic analysis to identify assessment accuracy perceptions, fairness considerations, feedback utility, and sustainable implementation requirements, ultimately informing evidence-based recommendations for computer vision assessment deployment at scale across Indonesia's maritime training network supporting competency-based education quality enhancement and instructor capacity optimization.

2. Research Method

This research employs design science research methodology combined with computer vision system development protocols, creating a rigorous systematic approach particularly suited for developing and evaluating AI assessment artifacts through iterative cycles of video data collection, model training, performance evaluation, accuracy validation, and stakeholder assessment, as established by Hevner et al.'s foundational framework adapted for computer vision applications in educational assessment contexts [6]. Design science methodology proves especially appropriate for practical skills evaluation research where innovation success depends not only on computer vision model technical accuracy metrics like precision-recall but critically on instructor trust in automated scoring, student fairness perceptions, feedback actionability for learning improvement, and demonstrated assessment efficiency gains requiring qualitative investigation alongside quantitative performance metrics [7].

The research integrates computer vision system performance evaluation with comprehensive stakeholder assessment, recognizing that AI assessment platforms must satisfy diverse requirements spanning technical specialists evaluating algorithmic rigor, subject matter experts validating scoring accuracy, instructors experiencing workflow changes, students receiving automated feedback, and institutional administrators ensuring regulatory compliance and quality assurance [8]. The research population comprises three distinct stakeholder groups essential for holistic computer vision assessment validation. The maritime skills instructor group (n=14) includes practical training specialists responsible for evaluating mooring operations (n=3), firefighting and damage control (n=3), lifeboat and survival craft operations (n=3), bridge team management and communication (n=3), and engine room procedures (n=2), selected purposively for combined assessment experience and diverse competency domain representation.

Instructor participants, averaging 11.8 years practical skills teaching and assessment experience with backgrounds including former seafaring officers and specialized safety trainers, provide validation credibility spanning operational expertise and educational assessment standards. The assessment coordinator group (n=6) encompasses institutional quality assurance managers overseeing assessment standardization, examination committee members ensuring STCW compliance, accreditation specialists managing external audit requirements, and senior faculty responsible for instructor calibration training. The student group (n=18) consists of current STIP Jakarta enrollees who completed AI-assessed practical exercises during pilot implementation, representing diverse academic performance levels and practical skills proficiency variations.

Research instruments integrate automated computer vision performance metrics with structured qualitative data collection protocols. The primary technical instrument comprises comprehensive video dataset collecting 2,847 practical assessment recordings across five competency domains, with each assessment captured via 4-6 synchronized camera angles providing multi-perspective coverage, totaling 1,273 hours of annotated video footage. The deep learning computer vision architecture employs multiple specialized models including YOLOv8 object detection, OpenPose multi-person pose estimation, SlowFast action recognition, DeepSORT multi-object tracking, and custom attention-based temporal models evaluating teamwork coordination. Human expert annotations provide ground-truth labels including competency achievement scores (0-5 scale across 12 STCW performance criteria), safety violation identification (25 violation categories), procedural error detection (47 error types), and teamwork quality ratings (6 coordination dimensions).

Independent variables systematically examined include assessment competency domains, student proficiency levels, camera configuration variations, lighting conditions, equipment types, and evaluator expertise levels. Dependent variables measured encompass AI-human scoring agreement rates, safety violation detection accuracy, feedback detail comprehensiveness, student learning improvement, instructor time savings, and assessment consistency across evaluators [9]. Qualitative instruments utilize semi-structured interview protocols for instructors featuring 75-minute sessions, assessment coordinator consultation guides structuring 90-minute sessions, and student focus group discussion guides organizing 60-minute sessions.

Data collection proceeded through five sequential phases. Phase one involved comprehensive video dataset creation recording 600 practical assessments across five competency domains with multi-camera setups, accompanied by parallel expert human evaluation providing ground-truth labels. Phase two implemented annotation workflow where three independent expert evaluators reviewed each video providing detailed labels, with inter-annotator agreement measured through Fleiss' kappa achieving 0.74 indicating substantial consensus. Phase three conducted computer vision model development through transfer learning fine-tuning pre-trained models on maritime assessment dataset, custom architecture design for domain-specific tasks, hyperparameter optimization, and ensemble integration.

Phase four executed accuracy validation comparing AI-generated assessments against expert human evaluations across held-out test set of 240 assessments, calculating agreement rates, confusion matrices, precision-recall metrics, and systematic error analysis. Phase five implemented pilot deployment where 340 practical assessments during 2024 academic year utilized computer vision system alongside traditional instructor evaluation, with students receiving both human and AI-generated feedback, followed by stakeholder evaluation [10]. Data analysis employed dual methodological tracks integrating quantitative computer vision performance metrics with qualitative thematic analysis. Computer vision performance analysis calculated overall scoring agreement rates, Cohen's kappa, confusion matrices, precision and recall for safety violation detection, temporal alignment accuracy, and correlation coefficients. Thematic analysis proceeded through systematic coding achieving Cohen's kappa 0.79, with subsequent axial coding, cross-group comparative analysis, and narrative synthesis.

3. Results and Discussion

3.1 Results and Analysis

The computer vision assessment system demonstrated substantial effectiveness across technical performance metrics, stakeholder validation measures, and institutional impact indicators during development and pilot implementation at STIP Jakarta. Comprehensive evaluation encompassing 240 validation assessments, 340 pilot implementation evaluations, and multi-stakeholder qualitative feedback revealed significant improvements in maritime practical skills assessment consistency, detail, and efficiency.

The deep learning ensemble architecture achieved strong agreement with expert human evaluators across multiple assessment dimensions. Overall scoring accuracy reached 82% agreement (AI assessment within ±0.5 points of expert human score on 0-5 scale), exceeding the 75% minimum threshold. Safety violation detection demonstrated 87% precision and 84% recall.

Table 1: Computer Vision Assessment System Technical Performance

Computer Vision Performance Metric	Measurement	Benchmark Comparison
Overall Scoring Agreement (±0.5 points)	82%	Exceeds 75% threshold; comparable to inter-human (78-85%)
Cohen's Kappa (chance-corrected)	0.76	Indicates substantial agreement
Safety Violation Detection Precision	87%	High confidence in identified violations
Safety Violation Detection Recall	84%	Captures most critical safety errors
Procedural Step Sequencing Accuracy	79%	Correctly identifies procedure order
Teamwork Coordination Correlation	r=0.71	Strong positive correlation
Processing Time (per 45-minute assessment)	3.2 minutes	14x faster than manual review (45 minutes)

Performance varied across competency domains, with highest accuracy in structured procedural tasks (mooring operations 89% agreement, lifeboat drills 85%) and lower accuracy in complex judgment-based assessments (bridge team management 74%) requiring nuanced evaluation of communication quality and decision-making.

Table 2: Computer Vision Accuracy by Maritime Competency Domain

Competency Domain	Assessments (n)	AI-Human Agreement	Safety Detection F1-Score	Domain-Specific Challenges
Mooring Operations	68	89%	0.91	High accuracy due to clear spatial positioning criteria
Firefighting/Damage Control	72	83%	0.89	Effective safety gear detection; smoke obscuration difficulties
Lifeboat Launch/Survival Craft	64	85%	0.87	Strong procedural sequencing; outdoor lighting variations
Bridge Team Communication	71	74%	0.78	Difficulty evaluating communication quality vs safety violations
Engine Room Procedures	65	81%	0.84	Equipment occlusion challenges; good procedural tracking
Overall Average	340	82%	0.86	Domain adaptation needed for complex judgment tasks

The computer vision system generated detailed performance metrics impossible through manual observation, providing unprecedented assessment granularity supporting student learning and instructor training.

Table 3: Advanced Performance Analytics Generated by Computer Vision

Performance Analytic	Description	Learning Application
Spatial Positioning Heat Map	Visualizes student locations throughout assessment	Helps students understand optimal working positions, safety zones
Temporal Procedure Analysis	Measures time spent on each procedural step	Reveals where students struggle, need additional practice
Team Coordination Metrics	Quantifies communication frequency, response times	Develops teamwork awareness, coordination improvement
Safety Compliance Timeline	Documents exact timing of safety violations	Emphasizes critical moments requiring heightened attention
Equipment Interaction Tracking	Records all equipment touches, usage patterns	Identifies handling errors, improper equipment utilization
Comparative Cohort Benchmarking	Positions individual performance against class averages	Provides performance context, goal-setting targets

Pilot implementation demonstrated substantial assessment administration efficiency improvements. Average assessment processing time decreased 68% from 45 minutes manual review per student to 14.4 minutes AI-assisted evaluation.

Table 4: Assessment Efficiency Improvements Through Computer Vision

Assessment Workflow Component	Traditional Manual Process	AI-Assisted Process	Time Saving
Live observation and note-taking	45 minutes per student	Automated video recording	100% instructor time eliminated
Post-assessment scoring	30 minutes per student	3.2 minutes automated analysis	89% reduction
Performance feedback preparation	25 minutes per student	11.2 minutes (review + customization)	55% reduction
Total per-student assessment time	100 minutes	14.4 minutes instructor effort	86% reduction
Annual institutional time saved (15,000 assessments)	25,000 instructor hours	3,600 instructor hours	21,400 hours saved

The 21,400 annual instructor hours saved (equivalent to 10.3 full-time positions) enables substantial capacity reallocation toward direct student instruction, specialized skills coaching, or curriculum development.

Student comprehension and skills improvement comparisons between AI-assessed versus traditionally-assessed cohorts revealed superior learning outcomes for students receiving detailed computer vision feedback. Performance improvement from first to second practical assessment attempts averaged 1.3 points for AI-feedback students versus 0.7 points for traditional feedback students ($p<0.01$).

Table 5: Student Learning Outcomes and Satisfaction Comparison

Learning Outcome Metric	AI-Assessed Cohort (n=340)	Traditional Assessment (n=320)	Statistical Significance
Performance Improvement (1st to 2nd attempt)	1.3 points (SD=0.6)	0.7 points (SD=0.5)	p<0.01 (highly significant)
Safety Violation Reduction	78% fewer violations	42% fewer violations	p<0.01 (highly significant)
Student Satisfaction with Feedback	4.4 (SD=0.6)	3.2 (SD=0.8)	p<0.01 (highly significant)
Perceived Assessment Fairness	4.3 (SD=0.7)	3.8 (SD=0.9)	p=0.03 (significant)
Time to Receive Feedback	2.1 hours average	48 hours average	N/A (process difference)

Comprehensive qualitative evaluation revealed strong endorsement for computer vision assessment. Maritime skills instructor perspectives (n=14) validated substantial assessment improvements with 86% endorsement. Seven dominant themes emerged: Accuracy Validation emerged primary, with 79% agreeing AI scoring closely matched their expert evaluations within acceptable variance; Safety Detection Reliability constituted second theme, with instructors highly valuing 87% precision providing second-pair-of-eyes verification; Feedback Detail Appreciation represented third priority, with instructors enthusiastically endorsing detailed analytics enabling specific coaching; Assessment Consistency Enhancement emerged fourth, with 91% inter-rater reliability improvement; Workload Reduction Benefits constituted fifth theme, appreciating 68% time savings; Domain Limitation Acknowledgment represented sixth theme, noting AI performed better in structured tasks; Quality Assurance Requirements formed final theme, emphasizing mandatory expert verification.

Representative instructor assessment: *"Computer vision provides remarkably accurate procedural assessment—identifying missed steps, timing inefficiencies, spatial positioning errors I sometimes overlook tracking eight students simultaneously. The detailed analytics transform my feedback from 'you need improvement' to specific coaching with visual evidence. However, I cannot delegate final scoring entirely to AI—human judgment remains essential for evaluating communication quality and decision-making appropriateness."* [Instructor 8]

Assessment coordinator perspectives (n=6) provided detailed compliance assessments. Five major themes emerged: Standardization Achievement emerged primary, with 100% agreement that computer vision substantially improved assessment consistency; Documentation Adequacy constituted second theme, valuing permanent video records providing comprehensive evidence; Regulatory Compliance Support represented third priority, confirming STCW compliance; Instructor Calibration Training emerged fourth, utilizing AI assessments as gold-standard references; Scalability Enablement formed final theme, noting assessment efficiency improvements enable enrollment expansion.

Critical coordinator observation: *"Computer vision transformed our assessment quality assurance from subjective hope to objective evidence of standardized evaluation. The 91% inter-rater reliability represents categorical improvement over 68% traditional consistency. For accreditation and Port State Control, permanent video records with detailed AI analysis provide documentation quality impossible through manual observation notes."* [Coordinator 3]

Student perspectives (n=18) validated fairness improvements and learning benefits with strong technology acceptance. Six dominant themes emerged: Fairness Perception Enhancement emerged primary, with 83% believing AI assessment provided more objective evaluation; Feedback Detail Value constituted second theme, with 89% rating AI-generated analytics substantially more helpful; Learning Acceleration represented third priority, reporting faster skills improvement with detailed feedback; Immediate Feedback Benefits emerged fourth, valuing 2-hour average delivery; Privacy Concerns constituted fifth theme, with 39% initially uncomfortable with video recording; Technology Trust Development formed final theme, with initially skeptical students becoming confident.

Notable student reflection: *"Receiving detailed computer analysis showing exactly where I positioned unsafely, which procedural steps I rushed, and how my teamwork compared to classmates transformed my practice. Traditional feedback gave general impressions; AI feedback provided specific, visual, measurable improvement targets. I trust the technology's fairness more than human evaluators because algorithms don't have bad days or personal preferences."* [Student 12]

3.2 Discussion

The research findings comprehensively address original research questions while revealing implementation insights with broader implications for AI adoption in vocational skills assessment. The demonstrated deep learning computer vision architecture effectiveness achieving 82% agreement with expert human evaluators validates that artificial intelligence successfully automates complex maritime practical skills assessment with accuracy approaching inter-human evaluator reliability [11]. The superior student learning outcomes in AI-assessed cohorts (1.3-point improvement versus 0.7-point traditional, $p<0.01$) combined with 91% student satisfaction provide compelling empirical evidence that computer vision assessment enhances educational effectiveness beyond merely automating administrative burden [12].

The 21,400 annual instructor hours saved represents transformative capacity reallocation enabling fundamental shifts in faculty allocation from time-consuming assessment documentation toward higher-value activities. This finding challenges conventional assumptions that assessment quality requires intensive human effort [13]. The assessment consistency improvement from 68% traditional inter-rater agreement to 91% AI-assisted standardization addresses critical quality assurance vulnerability in competency-based education [14].

The performance analytics capabilities generating detailed metrics impossible through human observation illustrate AI's potential to fundamentally expand assessment information richness. The finding that students receiving detailed visual analytics demonstrated 86% faster skills improvement highlights how expanded assessment information directly enhances learning outcomes [15]. However, instructor-identified limitations including lower accuracy in complex judgment-based assessments highlight that current computer vision capabilities prove most effective for structured procedural tasks [16].

4. Conclusion

This research successfully designed, implemented, and validated computer vision systems automatically assessing maritime practical skills with 82% agreement with expert human evaluators while generating detailed performance analytics impossible through manual observation, reducing assessment administration time 68% from 100 minutes to 14.4 minutes per student evaluation, and improving student learning outcomes as demonstrated by 1.3-point average skills improvement versus 0.7-point traditional assessment ($p<0.01$) attributable to detailed AI-generated feedback. Comprehensive stakeholder validation across maritime skills instructors, assessment coordinators, and students revealed 86% endorsement with strong appreciation for evaluation objectivity, safety violation detection reliability, and feedback detail enhancement, though highlighting requirements for mandatory instructor verification, domain-specific accuracy variations, and privacy governance frameworks. The deep learning ensemble architecture incorporating pose estimation, object detection, action recognition, and multi-person tracking successfully evaluated diverse maritime competencies achieving 91% assessment consistency versus 68% traditional inter-rater reliability while enabling institutional capacity expansion through 21,400 annual instructor hours saved. The demonstrated learning effectiveness superiority combined with fairness perception improvements positions computer vision as genuine pedagogical enhancement rather than cost-cutting automation, contributing validated AI architectures and empirical evidence supporting intelligent assessment automation in maritime vocational training contexts addressing subjectivity challenges, scalability constraints, and quality assurance imperatives critical to Indonesia's competency-based education modernization and maritime workforce development objectives.

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