SAGES 2026
March 25-28
Tampa Convention Center | Tampa, Florida

Surgical Video "Highlights Reel" Generation Based on AI-based Video Content Inference

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Introduction

Clinical Need
(Manual review bottleneck)

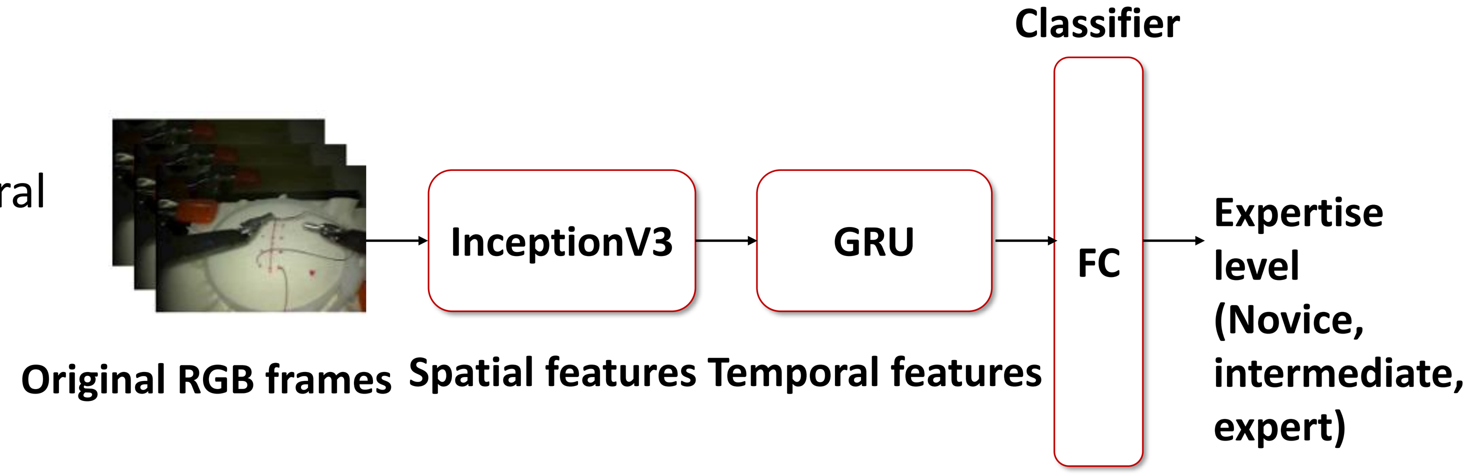
Importance
(Objective skill assessment & scalability)

Study Overview & Novelty
(AI-driven automated "highlight reels")

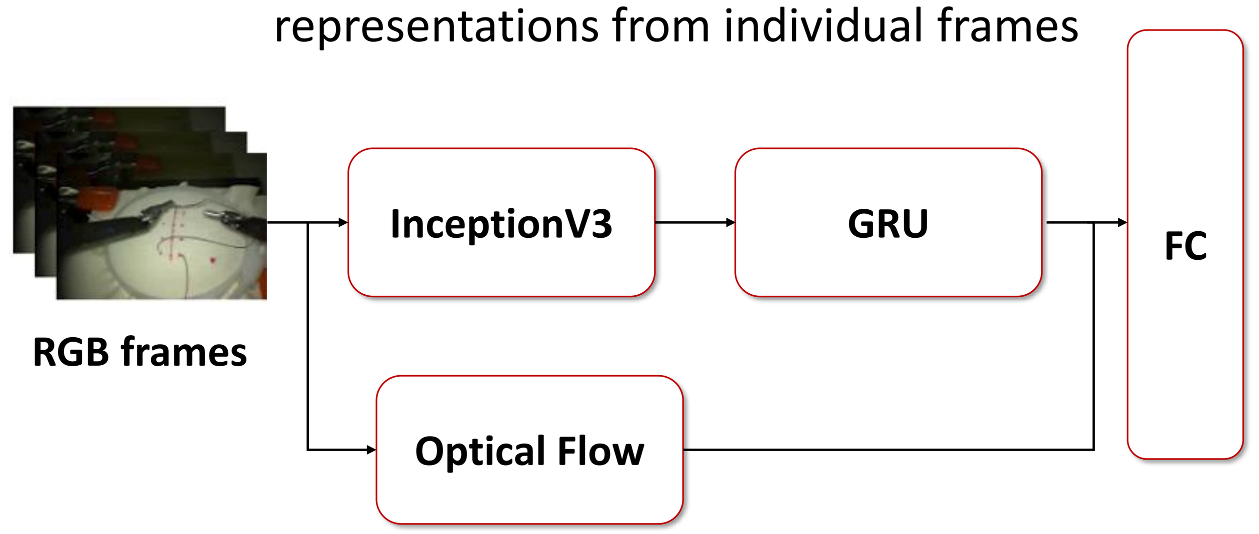
Materials & Methods

Hypothesis

Integrating spatial frame representations with temporal sequence modeling can accurately classify surgical expertise and automatically generate interpretable "highlight reels" of critical tool-tissue interactions.



Spatial features:
A pre-trained InceptionV3 extracted spatial representations from individual frames



Validation: On JIGSAWS dataset with established expertise labels (suturing 39 videos)

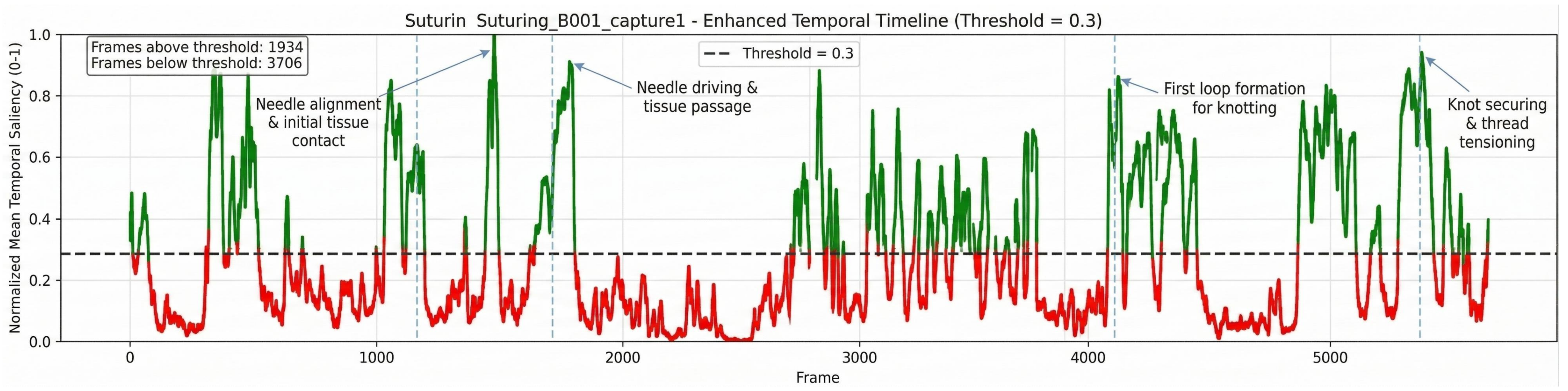
Temporal features:
A Gated Recurrent Unit (GRU) captured temporal dependencies, technique consistency and motion patterns across the video sequence

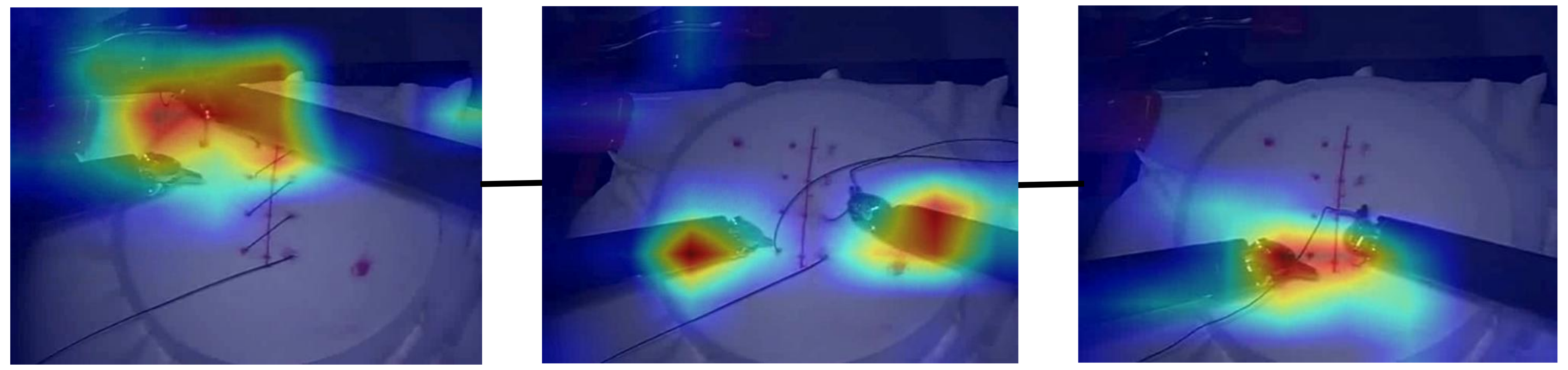
Classification: Fused spatiotemporal features are passed to a fully-connected classifier to output the expertise level.

Alternative Variant

- Evaluated a motion-augmented variant using late feature fusion of Optical Flow and RGB to capture bimanual coordination and motion smoothness.
- Underperformance

Results





Interpretability: Visualizing localized tool-tissue interactions

Table 1: Performance comparison.

	Accuracy	Macro Precision	Macro Recall	Macro F1	Class Expert	Class Intermediate	Class Novice
RGB	**0.9524**	**0.9420**	**0.9175**	**0.9234**	P: 0.861 R: 0.989 F1: 0.921	P: 0.990 R: 0.764 F1: 0.863	P: 0.975 R: 0.999 F1: 0.987
RGB+Optical-Flow	0.3803	0.6403	0.4911	0.3958	P: 0.244 R: 0.945 F1: 0.388	P: 0.851 R: 0.312 F1: 0.456	P: 0.826 R: 0.217 F1: 0.343

Model Performance

- The primary RGB pipeline achieved **95% classification accuracy**.
- Strong discrimination between novice and expert levels
- The motion-augmented variant underperformed (38% accuracy), heavily diluted by noisy Optical Flow from camera drift, glare, and phantom movement.

Conclusion

Findings & Impact

Our spatiotemporal pipeline accurately classifies surgical expertise and generates intuitive high-interpretability "highlight reels".

* This transforms clinician involvement by reducing manual review, maintaining capability and accelerating assessment.

Future Vision

Expansion to specific task-level metrics and longitudinal tracking of trainees

References

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Surgical Performance Enhancement and Robotics Centre (SuPER)