

FetNet: A Recurrent Convolutional Network for Occlusion Identification in Fetoscopic Videos

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Twin-to-Twin Transfusion Syndrome (TTTS)

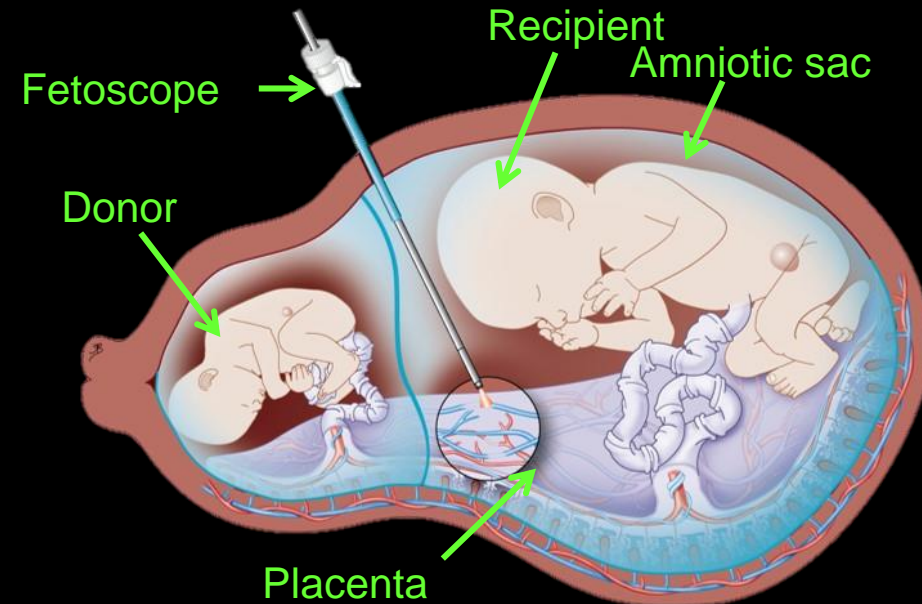
TTTS is a fetal anomaly affecting identical twins sharing a **monochorionic placenta**

Consequence

- Unbalanced flow of blood
- **Donor** may experience much slower growth
- **Recipient** at risk of heart failure

Common treatment

- Fetoscopic laser photocoagulation



Fetoscopic Laser Photocoagulation

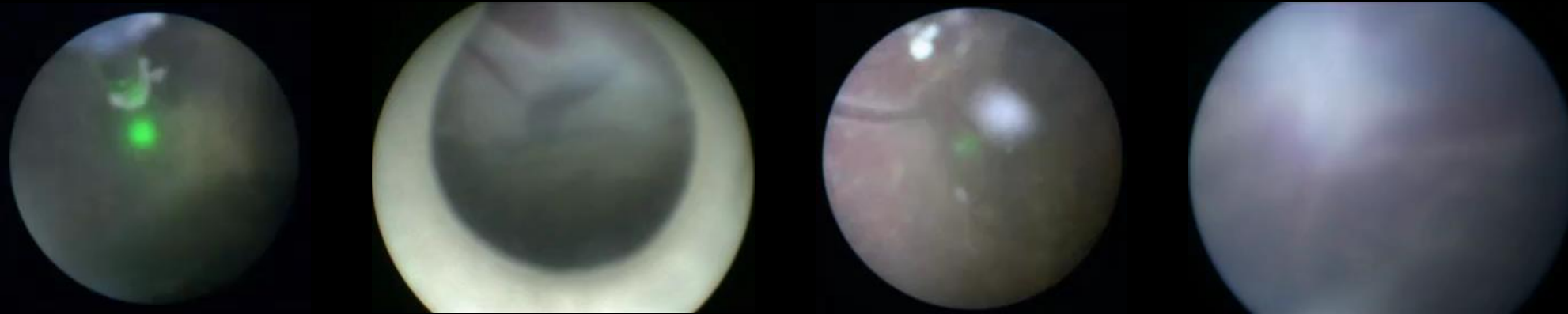
Fetoscopic laser photocoagulation is a **minimally invasive surgery**

- Visually **explore** the placenta using fetoscopic camera to **identify** vascular anastomose
- **Localize** the target vessels and use the laser to **ablate** them



Safe procedure requires

- **Clear view** of the placenta
- **Clear path** between the ablation tool and the target vessels



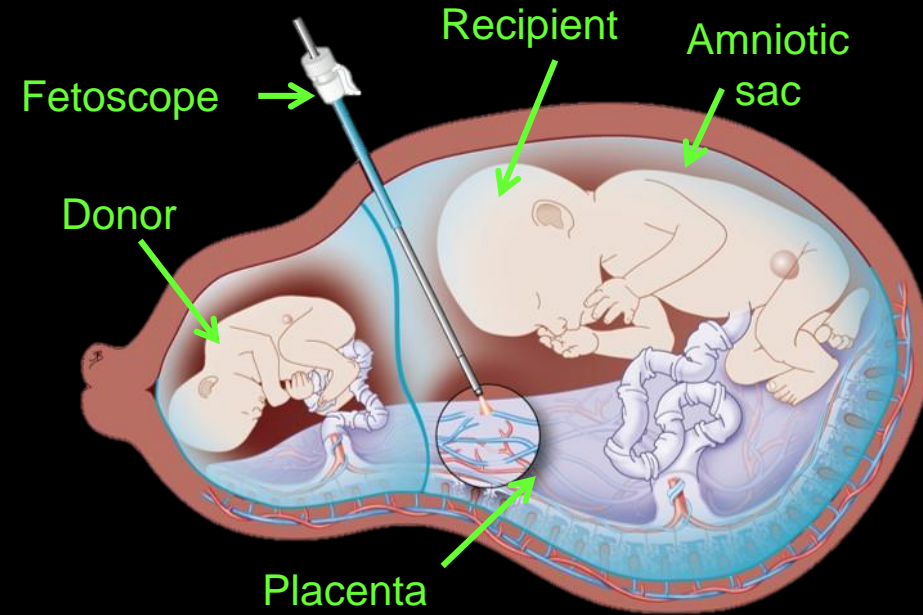
Difficult visual conditions

- Poor visibility (low resolution, low illumination, amniotic fluid turbidity)
- Occlusion due to the fetus and working channel port
- Specular highlights resulting in glare and reflection

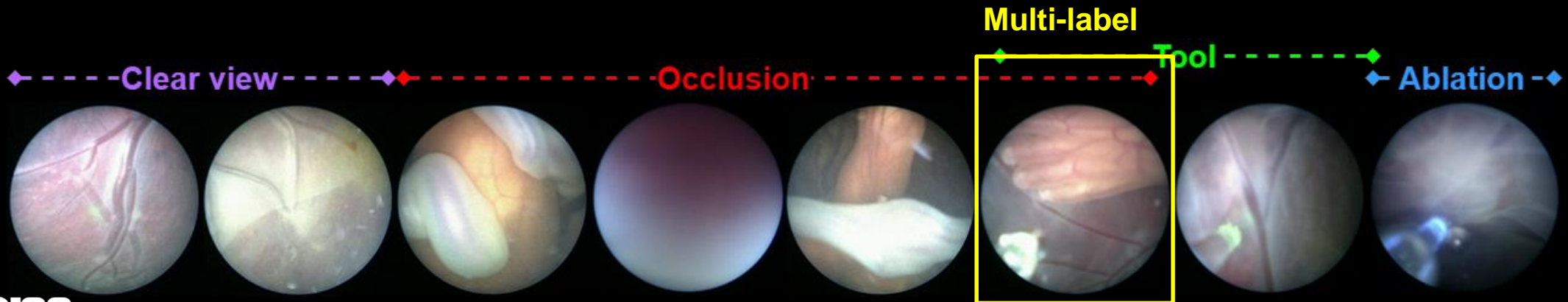
Fetoscopic Event Identification - Motivation

Identifying fetoscopic events can

- Assist surgeons during the TTTS procedure
- Provide context for navigation and mapping

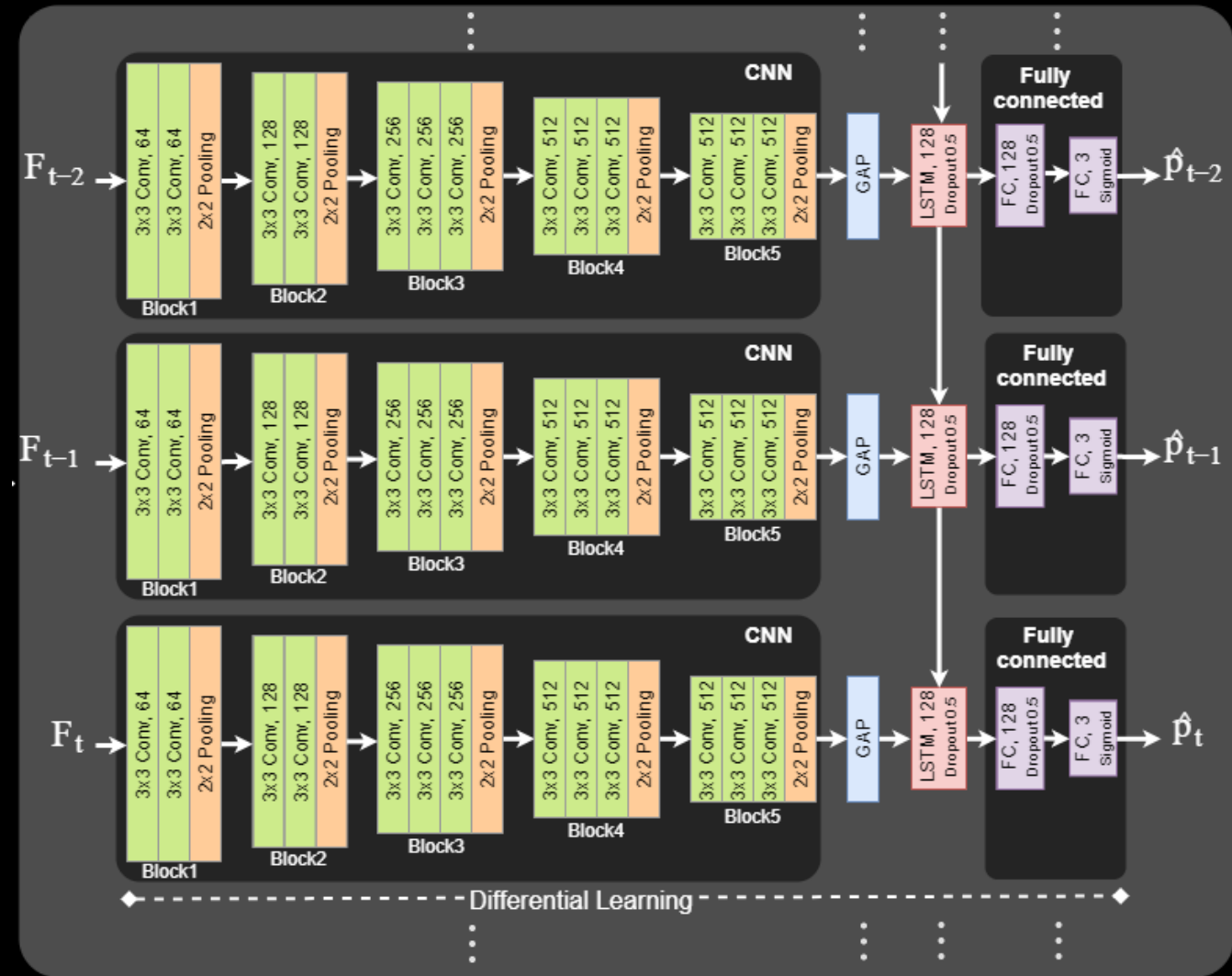


Four event labels created are



Proposed FetNet Architecture

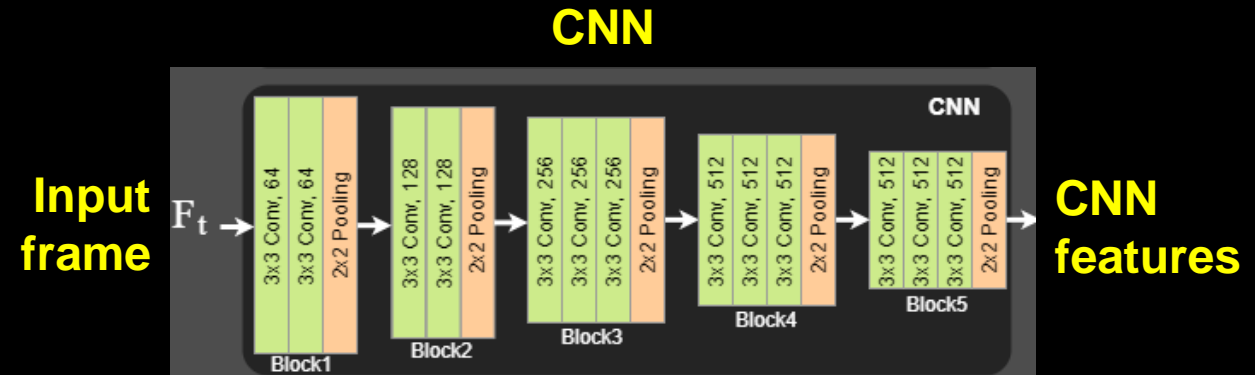
A recurrent convolutional network for spatio-temporal identification of fetoscopic events



Proposed FetNet Architecture

A recurrent convolutional network for spatio-temporal identification of fetoscopic events

- Integrates:
 - Convolutional Neural Network (CNN) for encoding spatial cues

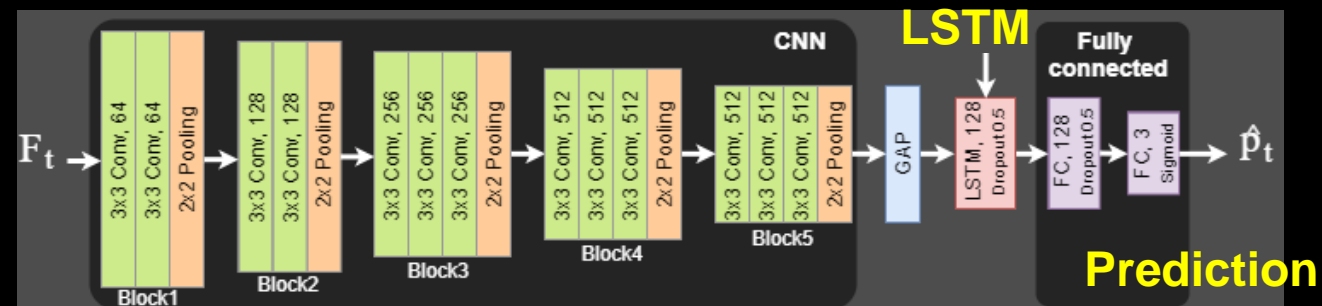


Proposed FetNet Architecture

A recurrent convolutional network for spatio-temporal identification of fetoscopic events

- Integrates:
 - Convolutional Neural Network (CNN) for encoding spatial cues
 - Long Short-Term Memory (LSTM) for encoding temporal cues
- Multi-labels handled using sigmoid activation
 - Independent prediction probabilities

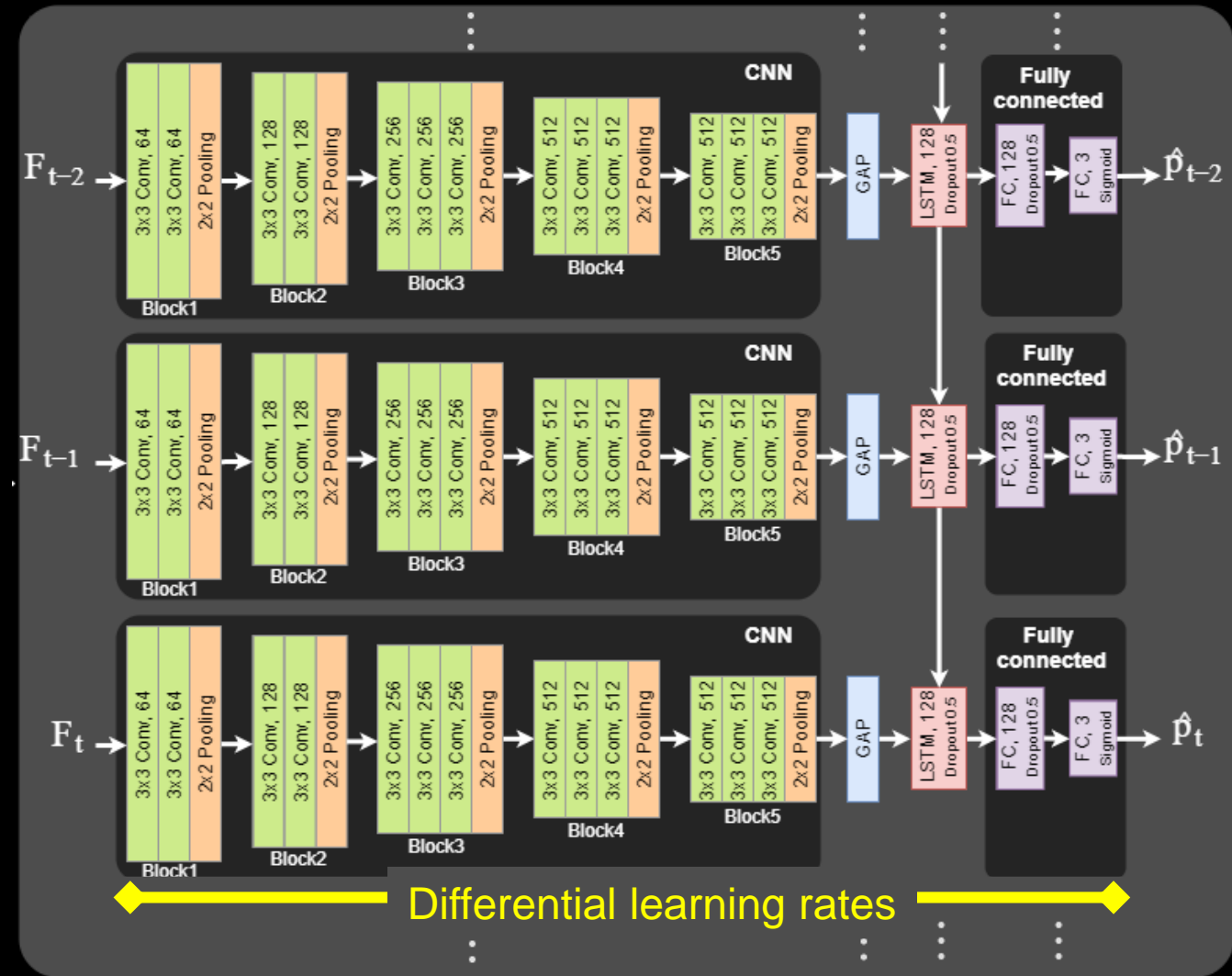
Input
frame



Proposed FetNet Architecture

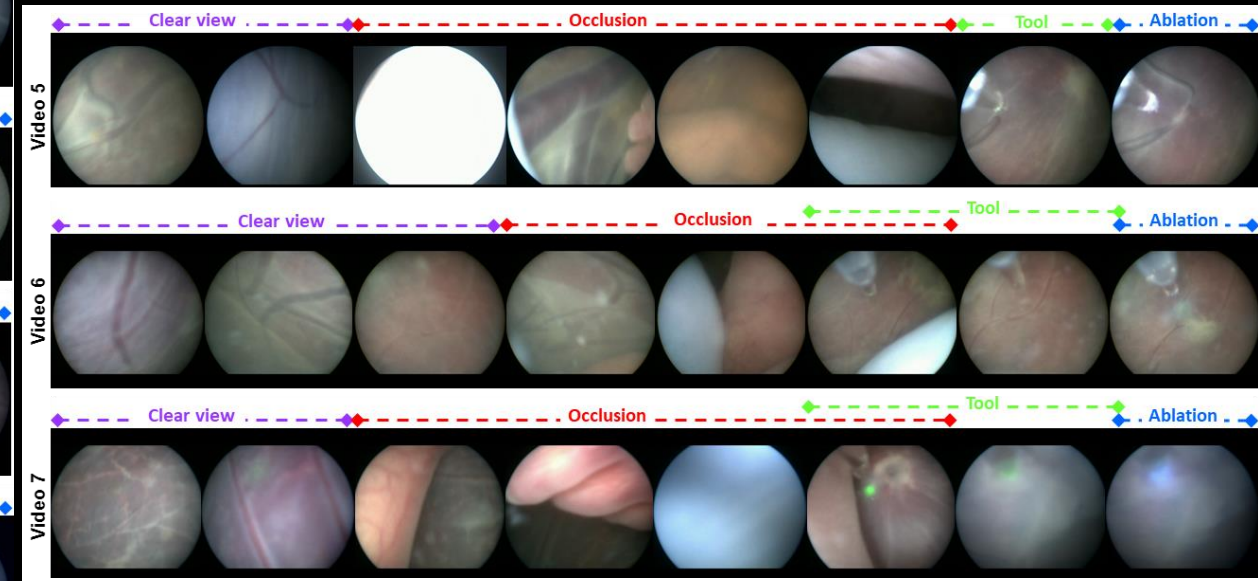
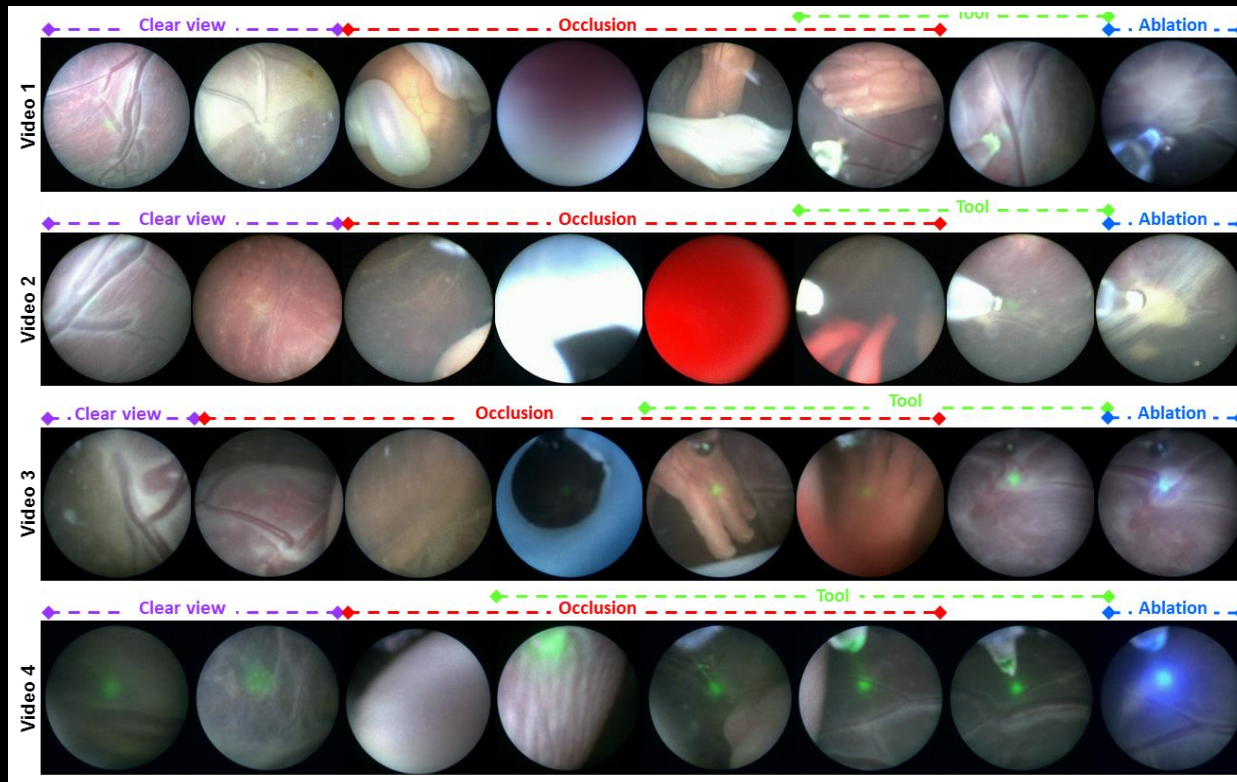
A recurrent convolutional network for spatio-temporal identification of fetoscopic events

- Integrates:
 - Convolutional Neural Network (CNN) for encoding spatial cues
 - Long Short-Term Memory (LSTM) for encoding temporal cues
- Multi-labels handled using sigmoid activation
 - Independent prediction probability
- Differential learning rates
 - Pretrained CNN weights



Dataset collection and annotation

- Seven fetoscopic videos from different patients
- Average duration of each video is 800s
- Frame-level manual annotation for events



Quantitative Analysis and Comparison

- 7-fold cross-validation

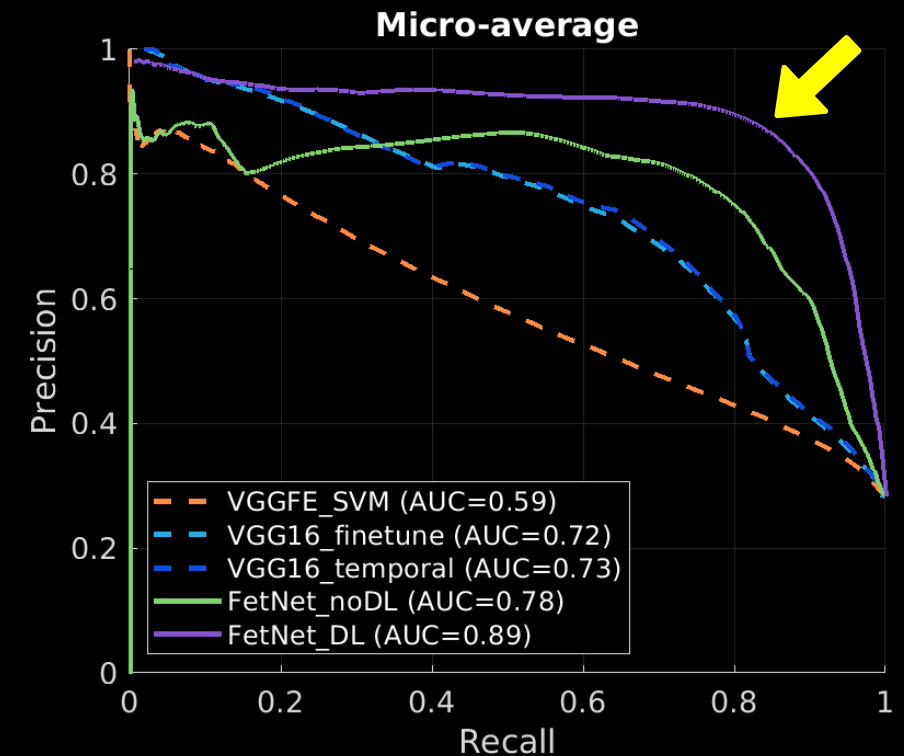
Comparison Methods

Ablation_detect	Fetoscopic ablation detection method [Vasconcelos_IJCAR2018]
VGGFE_SVM	CNN features with SVM classifier [Cadene_arXiv2016]
VGG16_fine	Fine-tuning of VGG16 [Simonyan_ICLR2015]
VGG16_temporal	Fine-tuning and temporal smoothing of VGG16 [Cadene_arXiv2016]
FetNet_noDL	Proposed without differential learning
FetNet_DL	Proposed with differential learning

Quantitative Analysis and Comparison

- 7-fold cross-validation

Class		Clear	Occlusion	Tool	Ablation	Average
Method						
Ablation_detect	Precision	-	-	-	0.81	0.81
	Recall	-	-	-	0.71	0.71
	F1-score	-	-	-	0.76	0.76
VGGFE_SVM	Precision	0.52	0.55	0.68	0.32	0.52
	Recall	0.42	0.70	0.50	0.19	0.45
	F1-score	0.46	0.62	0.58	0.24	0.47
VGG16_fine	Precision	0.66	0.69	0.76	0.96	0.77
	Recall	0.47	0.69	0.73	0.61	0.63
	F1-score	0.55	0.69	0.74	0.75	0.68
VGG16_temporal	Precision	0.72	0.70	0.76	0.96	0.79
	Recall	0.46	0.68	0.73	0.56	0.61
	F1-score	0.56	0.69	0.74	0.71	0.68
FetNet_noDL	Precision	0.72	0.70	0.86	0.95	0.81
	Recall	0.78	0.60	0.90	0.69	0.74
	F1-score	0.74	0.65	0.88	0.80	0.77
FetNet_DL	Precision	0.86	0.69	0.92	0.96	0.86
	Recall	0.84	0.79	0.94	0.95	0.88
	F1-score	0.85	0.74	0.93	0.95	0.87






Qualitative Analysis

Ground-truth label

Predicted probability

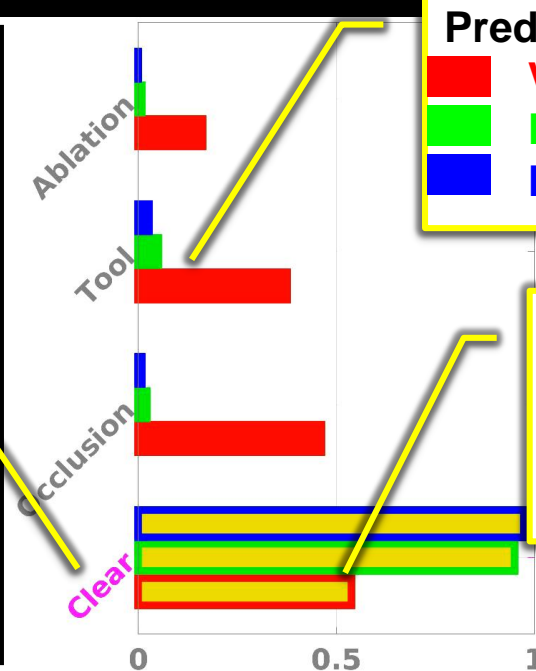
 VGG16_fine
 FetNet_noDL
 FetNet_DL

Predicted label

 VGG16_fine
 FetNet_noDL
 FetNet_DL



Ground-truth label



Predicted probabilities







 VGG16_fine
 FetNet_noDL
 FetNet_DL

Predicted labels

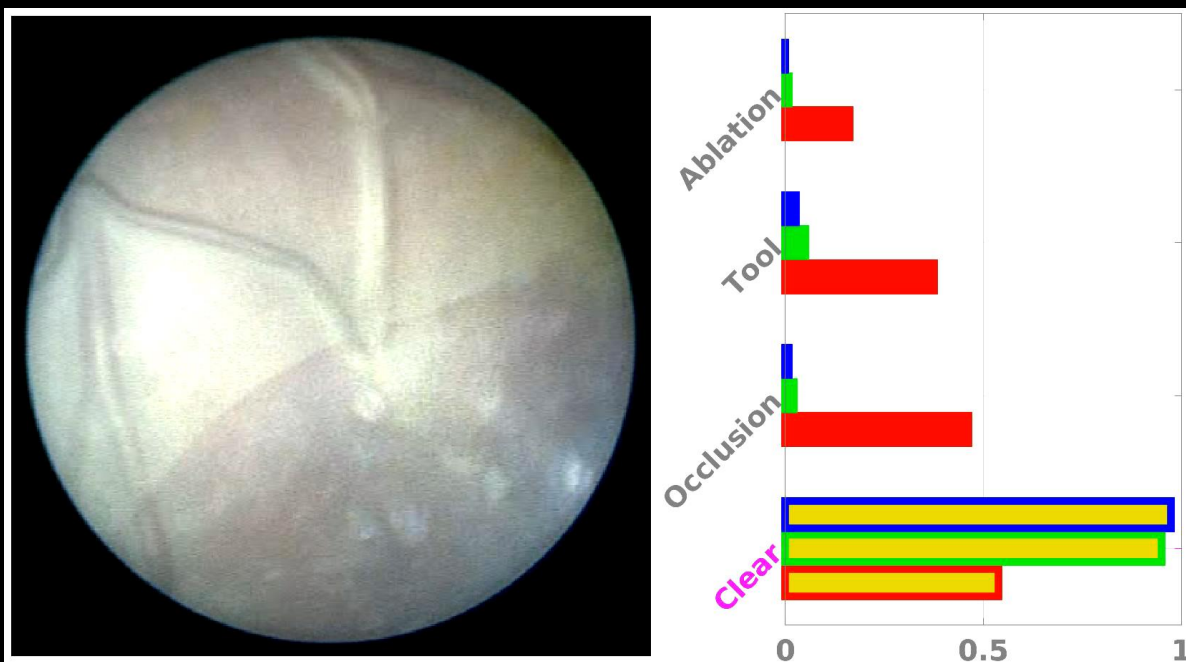
 VGG16_fine
 FetNet_noDL
 FetNet_DL

Qualitative Analysis

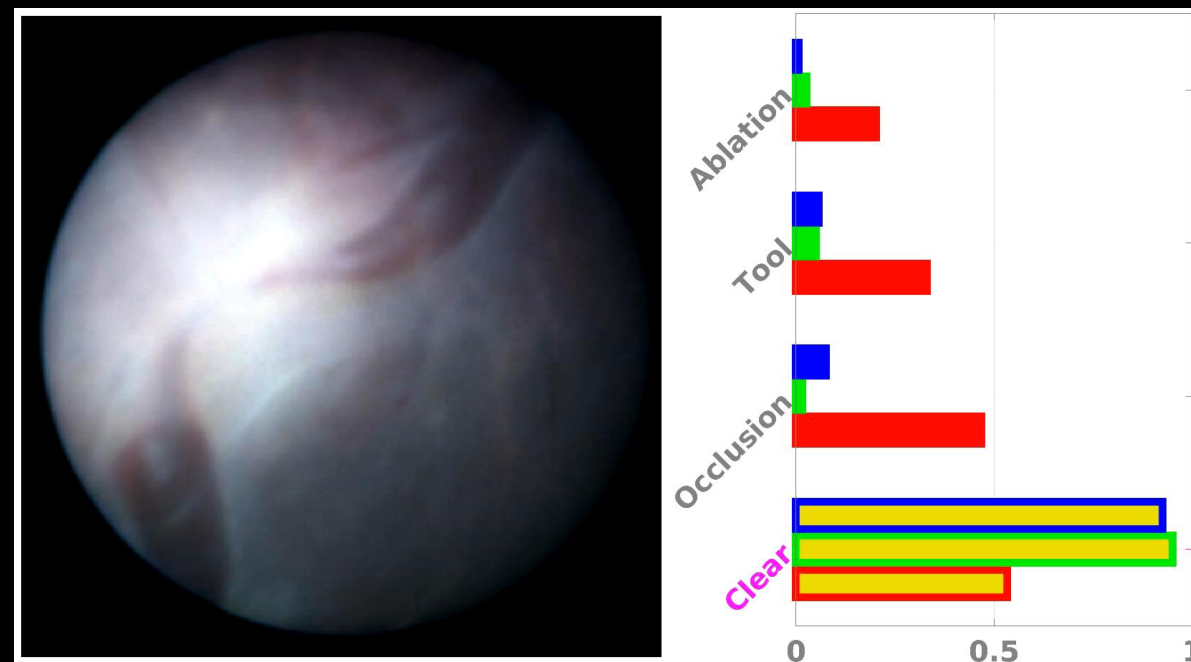
Single label per frame

Ground-truth label	
Predicted probability	
	VGG16_fine
	FetNet_noDL
	FetNet_DL
Predicted label	
	VGG16_fine
	FetNet_noDL
	FetNet_DL

Clip 1: Clear view or occlusion

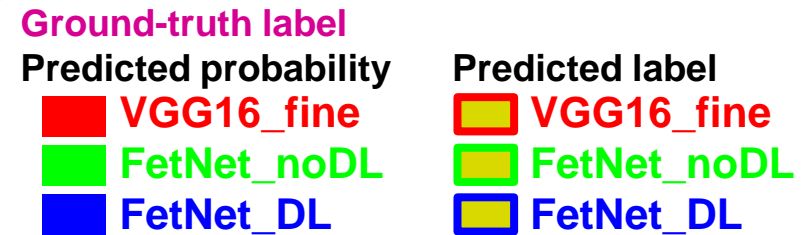


Clip 2: Tool or ablation

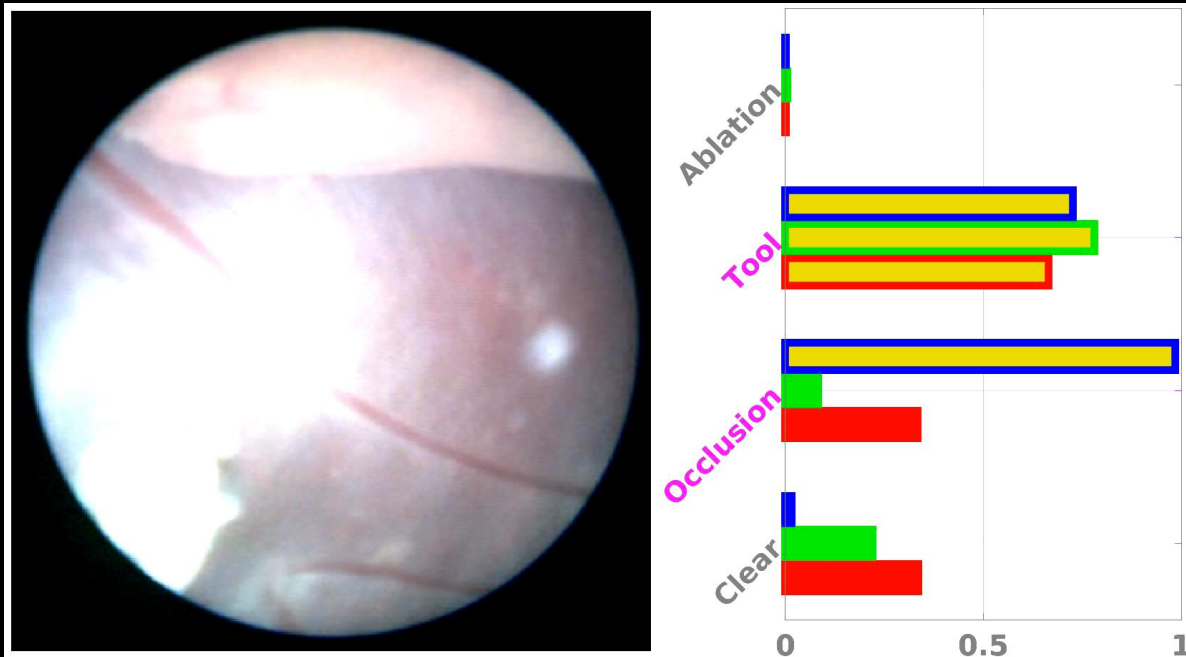


Qualitative Analysis

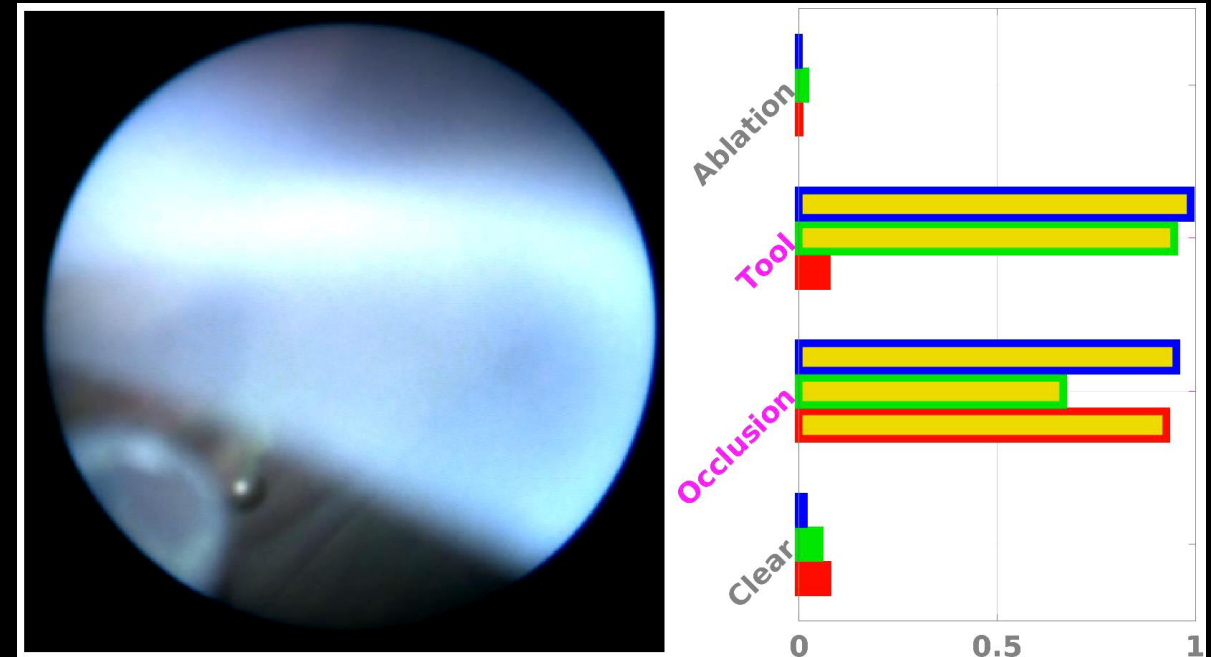
Multi-labels per frame



Clip 3: Occlusion and tool



Clip 4: Occlusion, tool and ablation

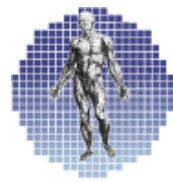


Proposed FetNet architecture

- Occlusion Identification in Fetoscopic Videos
- Obtained an overall F1-score of 87%
- Outperformed existing methods
- Online testing returned a frame rate of 114 *fps*

Future work

- Possible integration in real-world systems
- Clear view segmentations are suitable for the field-of-view expansion



CARS
Computer Assisted Radiology and Surgery

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Thank you

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