PROJECT PRESENTATION

DEEP ARCHITECTURE FOR OPTICAL FLOW ESTIMATION: RAFT

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Adem Dey
Achraf Habib

Supervised by
Rabaa Youssef, PhD

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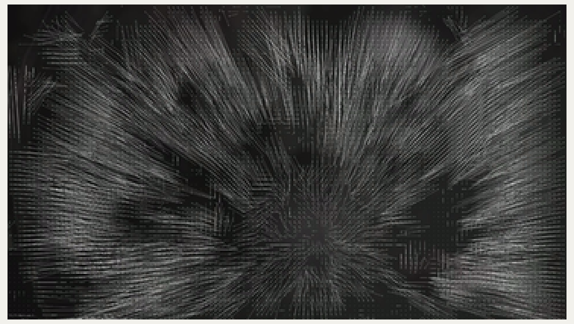
INTRODUCTION

problem and context

Optical flow estimation tracks motion between video frames, crucial for applications like autonomous driving, robotics, and video editing. However, it's challenging due to large motions, occlusions, and the need for real-time processing. Traditional methods often struggle with accuracy and speed. RAFT (Recurrent All-Pairs Field Transforms) solves these issues by

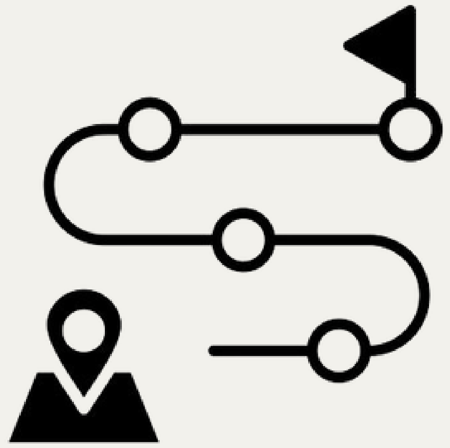
Matching all pixels across frames for precise motion and Leveraging a cost volume approach for efficient motion estimation, RAFT offers high accuracy and efficiency, making it ideal for real-world motion estimation.



1 INTRODUCTION

WHY RAFT

MECIAL PROBLEM



PROJECT MILESTONES

INTRODUCTION

Applications of RAFT:

1. **Autonomous Driving:** Helps detect and track objects in real time, supporting safe navigation.
2. **Robotics**: Enables accurate motion tracking for obstacle avoidance and interaction in dynamic environments.
3. **Medical Imaging**: Tracks movement within body scans (e.g., ultrasound) for better diagnostics.
4. **Video Post-Processing**: Improves stabilization, object tracking, and visual effects with precise motion estimation.

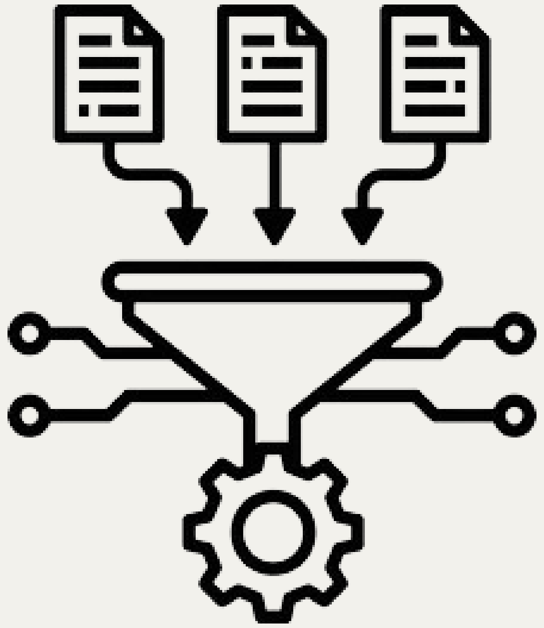
Benchmark Performance Examples:

- **KITTI Benchmark:** A popular benchmark for testing vision tasks in self-driving scenarios, KITTI evaluates models on their ability to handle realistic road scenes and large movements. RAFT's strong performance on KITTI shows its capability for real-world driving applications.
- **Sintel Benchmark:** A synthetic benchmark designed to test optical flow models on complex scenes, with varied lighting, textures, and occlusions. RAFT's success on Sintel demonstrates its ability to handle challenging and diverse visual environments, making it suitable for both real-world and artificial scenarios.

RAFT ARCHITECTURE

2 RAFT ARCHITECTURE

outline



DATA PREPARATION

MODEL SELECTION, TRAINING AND VALIDATION

2 RAFT ARCHITECTURE

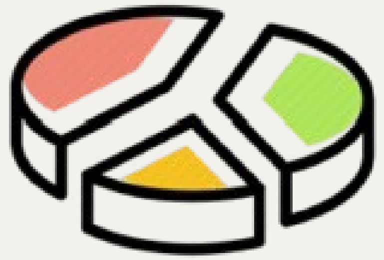
Data preparation

Data preparation

- **MIMIC III dataset** (46520 patients)
- **Data inclusion criteria**: stroke diagnosis, Age > 18, **vital signs availability**
- **One-hour aggregation**

Preproceesing steps

- **Temporal data splitting** (80\10\10)
- **Missing data imputation, scaling, data imbalance weightening**



Data annotation

IF (Non-Invasive SBP > 140 mmHg AND Non-Invasive DBP > 90 mmHg) THEN stroke = 1 ELSE stroke = 0 END

Sully Xiomara Fuentes Patarroyo and Craig Anderson. "Blood pressure lowering in acute phase of stroke: latest evidence and clinical implications". In: Therapeutic Advances in Chronic Disease 3.4 (July 2012), pp. 163–171.

RAFT ARCHITECTURE

Model selection, training and validation

Input data : Final pre-processed data: 1976 patients (CSV file)

HADM_ID	SUBJECT_ID	GENDER	AGE	Admission Weight (Kg)	Height (cm)	Heart Rate	Non Invasive Blood Pressure diastolic	Non Invasive Blood Pressure mean	Non Invasive Blood Pressure systolic	Respiratory Rate	Tachycardia	Bradycardia	Hypertension	Hypotension	Tachypnea	Bradypnea	stroke

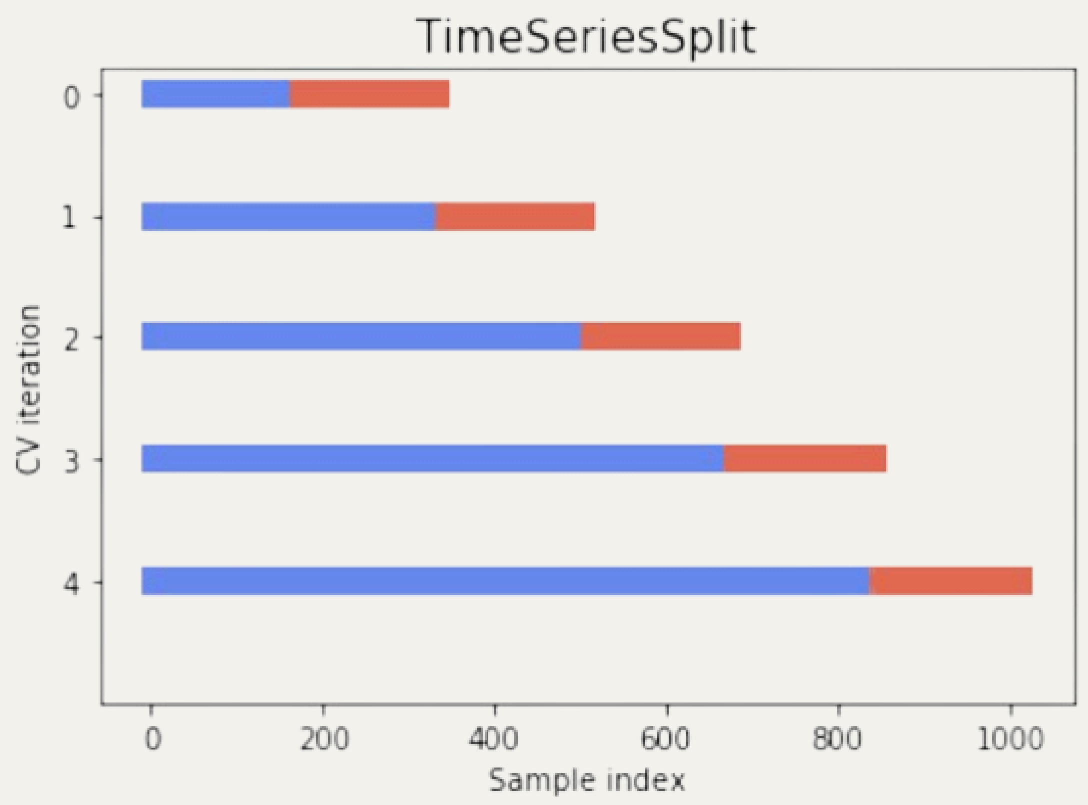
Output : Predicted stroke risk percentage

Model Selection

- **LSTM model :** Long Short-Term Memory
- **GRU model :** Gated Recurrent Unit
- **Custom model :** Tuned Bidirectional LSTM

Model validation

Cross-Validation method: TimeSeriesSplit



IMPLEMENTATION

3 IMPLEMENTATION

Here's The link to Our Google Collab Notebook :

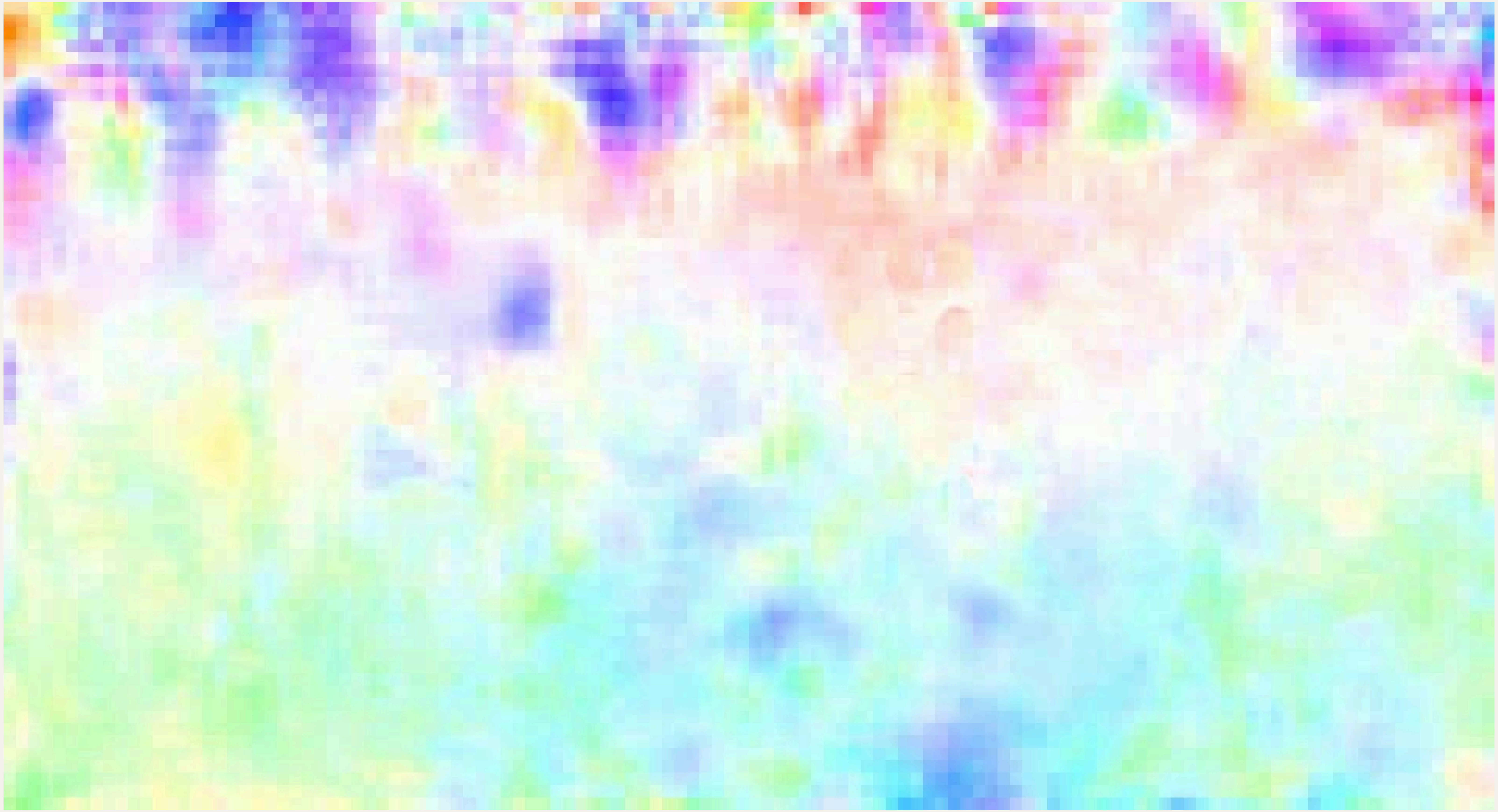
https://colab.research.google.com/drive/1OHvP_cljx4mGylneqBItlQDqYmKmEDQL?usp=sharing

3 IMPLEMENTATION

Primary tools used

- Pytorch
- Python
- Nvidia
- Google Collab

DEMO



3 RESULT ANALYSIS

The RAFT model shows varying sensitivity depending on the speed and clarity of motion in videos. For slow movements, like in the previous Video, it may produce **less accurate results**, while on faster sequences with more pronounced contrasts, it provides higher-quality optical flow visualizations.

For projects requiring precision with slow movements, it may be beneficial to explore alternatives .

GENERAL CONCLUSION

5 GENERAL CONCLUSION

Conclusion

In conclusion, t**he performance of RAFT** is generally impressive, especially on data that closely matches the conditions it was trained on. It excels in handling fast-moving sequences with high contrast, providing highly accurate optical flow estimations. However, its performance tends to decrease when dealing with slow-moving videos, where motion can be more subtle and harder to detect.

Additionally, **RAFT** may struggle with **occlusions** and **large displacements** in certain scenes, impacting accuracy.
The model also requires significant **computational resources** for real-time performance. 7
For scenarios involving slower movements or complex scenes, adjustments like tuning parameters or using specialized models may be needed. Despite these limitations, RAFT remains a powerful tool for motion estimation in dynamic environments.

THANK YOU FOR YOUR ATTENTION