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HANDOVER PREDICTION FOR NSA 5G SYSTEMS IN MARITIME ENVIRONMENTS USING MACHINE LEARNING

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FÖRDE 5G
PART OF CAPTN

Outline

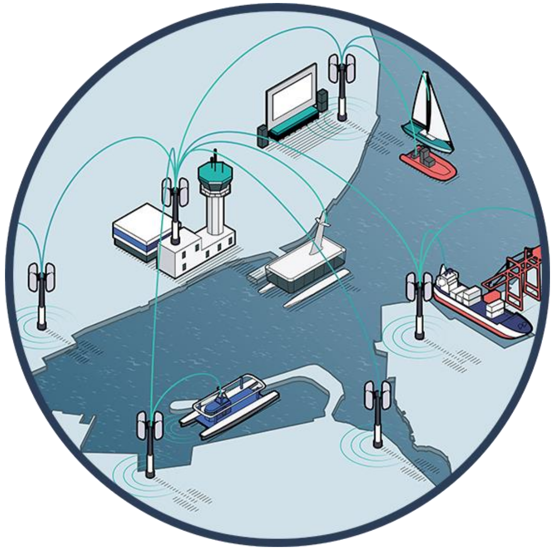
- Motivation
- Data Collection
- Machine Learning
- Results
- Conclusion & Outlook

Motivation

- Additional capabilities of 5G like enhanced mobile broadband (eMBB), massive machine-type communications (mMTC) and ultra-reliable low-latency communications (URLLC) allow autonomous & remote controlled vehicles to be deployed in more scenarios
- Increased vulnerability to latencies and connection failures during the handover process
- Can lead to potentially fatal accidents
- Additional issues in maritime scenarios considered here:
  - Larger distances to base stations
  - Different types of participants of various sizes, speeds and levels of vulnerability, in less controlled environment

→ Accurate handover prediction is necessary

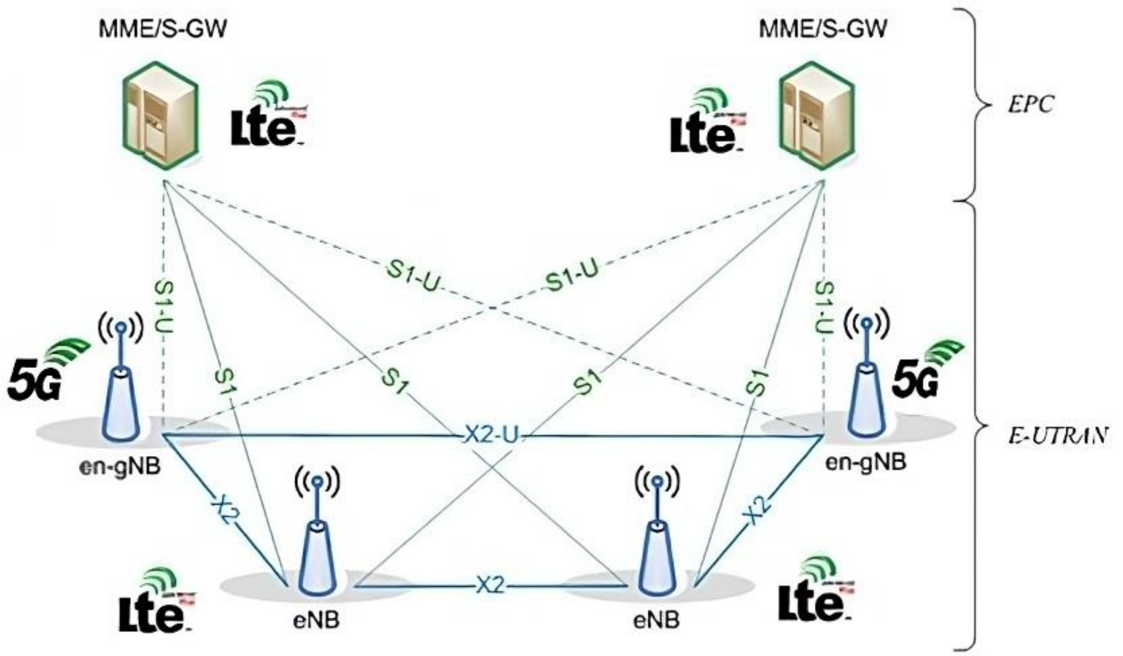
→ Use Machine Learning for this task



Crash between two ships earlier this year (DAPD/Dierk Boldt)

Non-Stand Alone (NSA) 5G

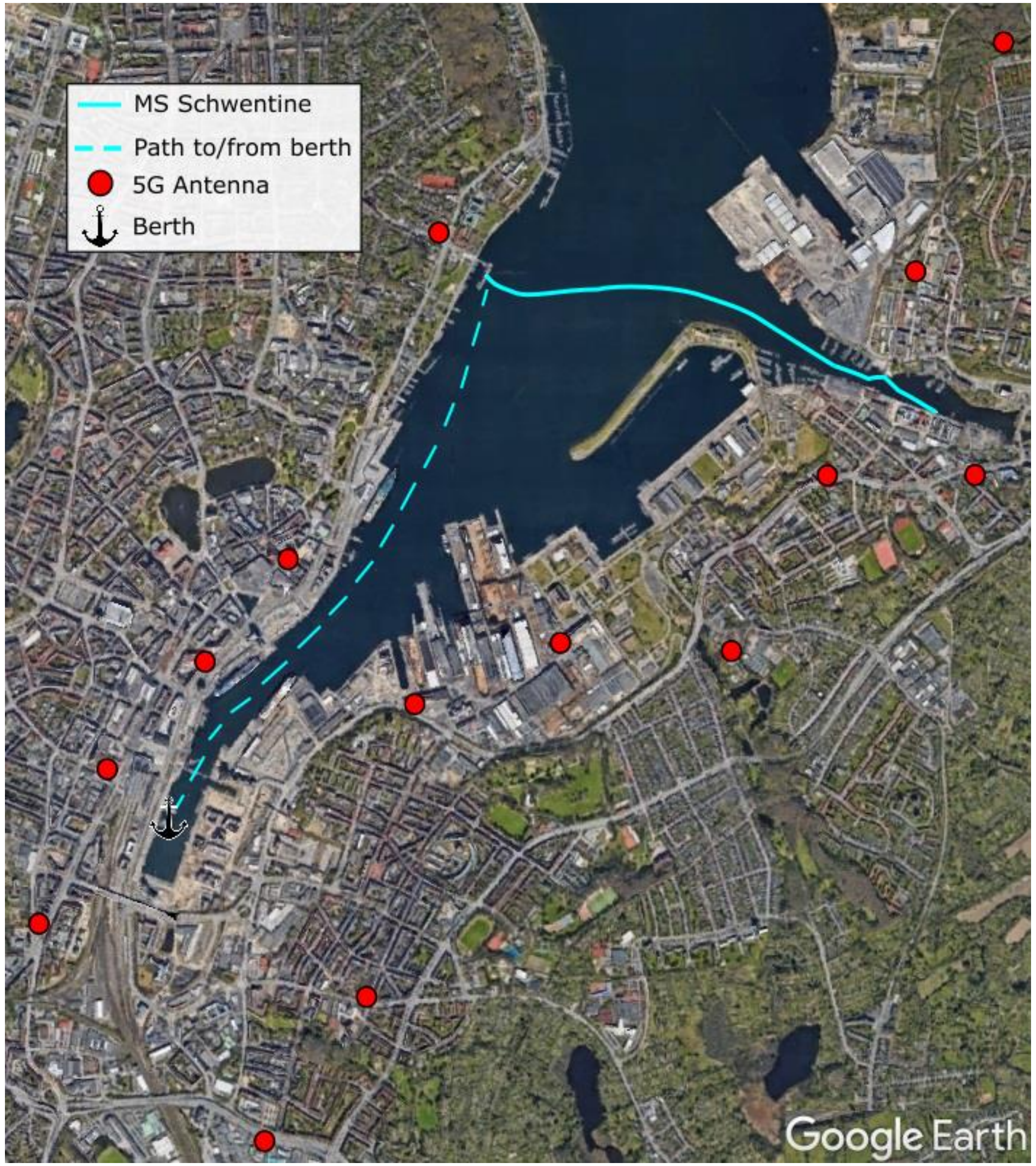
- Configuration of 5G where the 5G Access Network (AN) is used in combination with the LTE Core Network (CN)
- 5G base station (gNB) secondary node connected via an X2 link to an LTE base station (eNB) serving as the master node
- User equipment (UE) with the option of connecting to the 4G AN and the 5G AN (dual connectivity)



Non-stand alone (NSA) architecture (3GPP)

Experimental Data Collection

- Router with a Deutsche Telekom SIM-card on board of the MS Schwentine ferry
- Ferry with multiple trips across the Kieler Förde and back
- Measurement period: 6 days
- Router connects to 17 different cells across 14 different base station pairs operating in non-stand-alone (NSA) 5G



Long short-term memory (LSTM)

- Type of recurrent neural network (RNN) with gated structure
- 3 types of gates:
  - Forget gate: information from previous cell state forgotten
  - Input gate: new information used to update current state
  - Output gate: parts of the cell state serve as the output
- Advantages:
  + Gated structure to avoid exploding or vanishing gradient problem
  + Sensitive to order of time steps → good modeling long term dependencies
- Disadvantages:
  – Slow training
  – Require more memory to train

Convolutional neural network (CNN)

- Sliding filter moving over its input
- Convolution between an array of the input data and an array of weights (kernel)
- 1D-CNN: Convolution between the time series data and the filter vector applies a moving average
- Pooling layers deployed to reduce dimensionality, by reducing parameters and model complexity
- Advantages:
  + Faster training
- Disadvantages:
  – Not sensitive to order of time steps → difficulties at modeling long term dependencies

Machine Learning - Parameters

- Predict, if handover will occur during next second based on information from the past 100 seconds
- Dataset size: 25,336
- Training: 75%, Testing: 25%
- Imbalanced dataset only ~30% handovers
- Binary focal cross entropy with focusing parameter γ = 2 to counteract dataset imbalance
- Metric: F_1 score

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

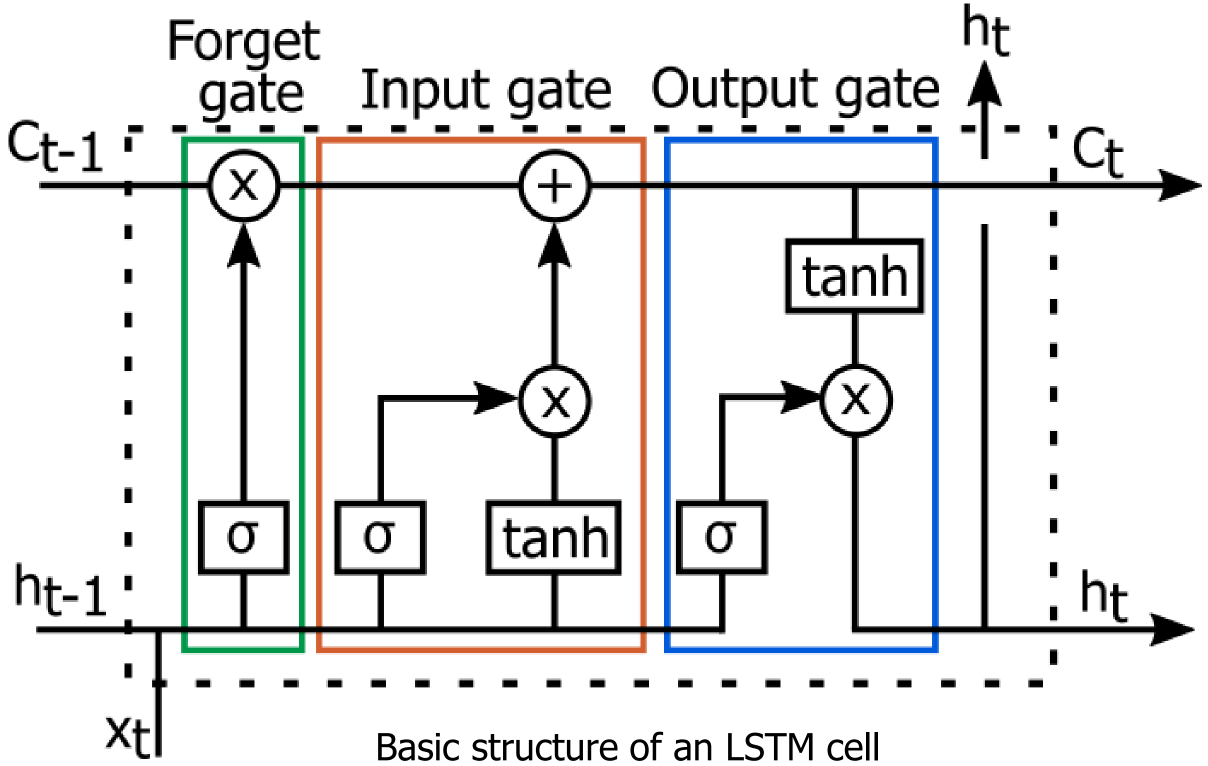
$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Features	Measured for
Latitude	Ferry
Longitude	Ferry
Altitude	Ferry
Channel quality indicator (CQI)	5G
Rank indicator (RI)	5G
Modulation and coding scheme (MCS)	5G
Cell ID	5G
Sector ID	5G
Signal-to-interference-and-noise ratio (SINR)	LTE & 5G
Reference signal receive quality (RSRQ)	LTE & 5G
Reference signal receive power (RSRP)	LTE & 5G
Reference signal strength indicator (RSSI)	LTE & 5G
Uplink modulation format	LTE & 5G
Downlink modulation format	LTE & 5G

Machine Learning - LSTM

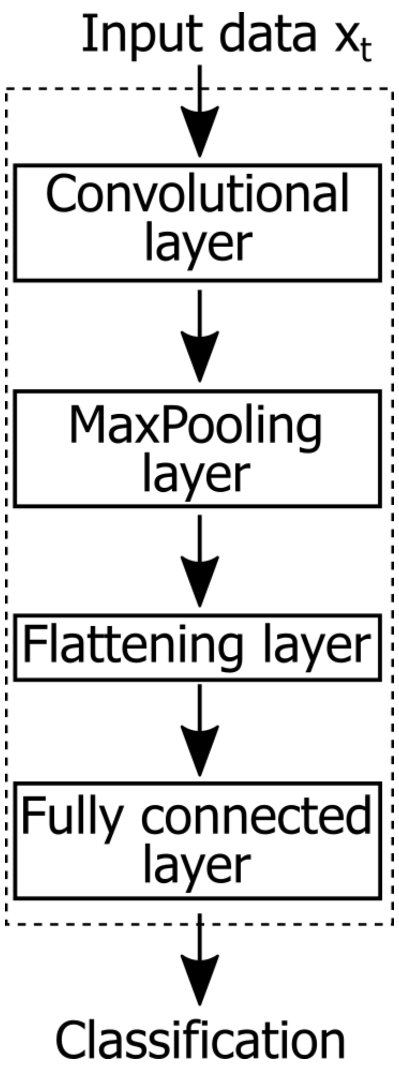
- LSTM with hand-selected parameters
- LSTM layer with 40 nodes
- Fully connected layer with a sigmoid activation σ
- Number of epochs: 150
- Batch size: 100
- x_t = Input features
- C_t = Cell state
- h_t = Output



Basic structure of an LSTM cell

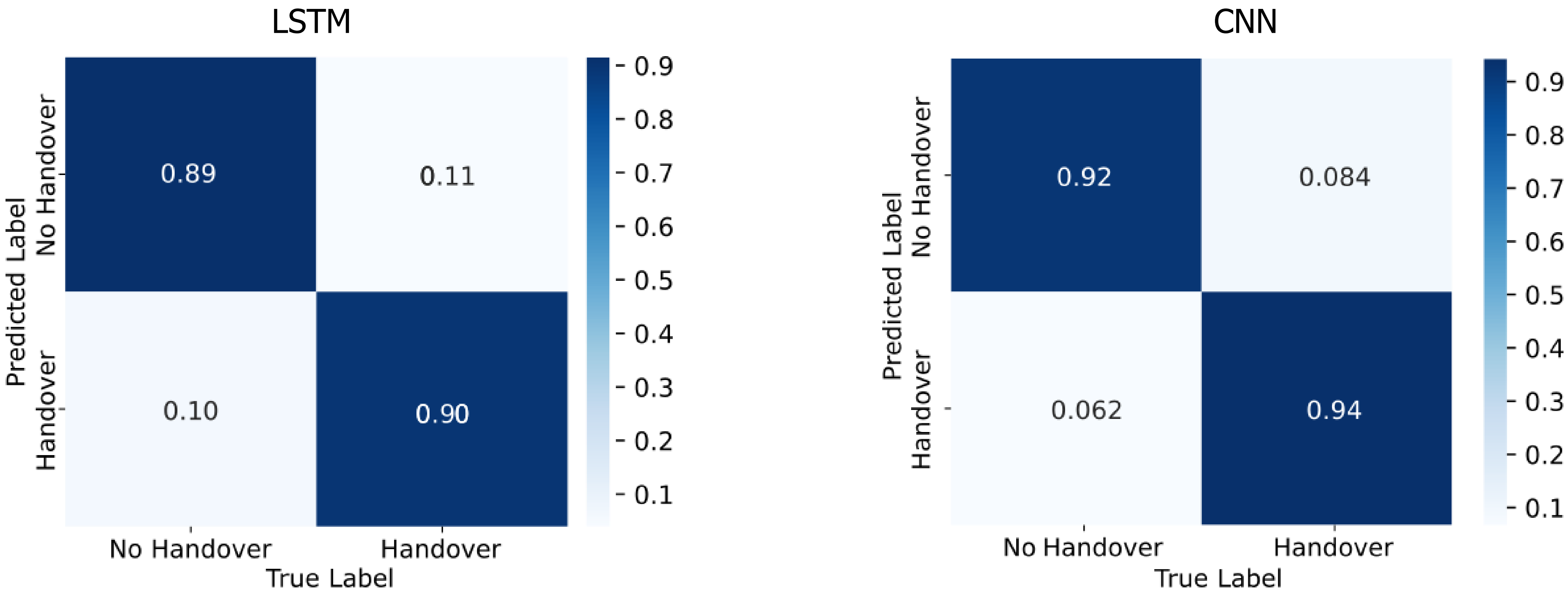
Machine Learning - CNN

- One-dimensional CNN with hand-selected parameters
- Convolutional layer with 150 filters
- Kernel size of 20
- Dropout layer, drops 20% of inputs to prevent overfitting
- One-dimensional maximum pooling layer with a pool size of 2
- Flattening layer to reduce dimensions
- Fully connected layer with a sigmoid activation σ
- Number of epochs: 150
- Batch size: 100



Structure of the CNN

- CNN achieves higher prediction results for both cases
- Both algorithms achieve slightly higher accuracy for the case with a handover



F1 score =0.8603042484972298

F1 score =0.9164637057141649

Conclusion & Outlook

- LSTM and CNN tested and compared in their capabilities to predict handovers
- Both algorithms achieve accuracy of at least 89%
- CNN outperforms LSTM
- Both algorithms show slightly increased accuracy for handover case
  - Focusing parameter probably set too large

- Parameter improvement via grid search or Bayesian hyper-parameter optimization
- Predictions further than 1 second into the future
- Additional consideration of Wi-Fi
- What can we do now that we have predicted the upcoming handover?
  - Handover failure prediction
  - Reaction to handovers by reducing amount of data sent and focusing on most important information
  - Evasion of unnecessary handovers

Thank you for the attention!

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