# **INDOOR LOCATION SENSING USING SMARTPHONE ACOUSTIC SYSTEM**

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## INTRODUCTION

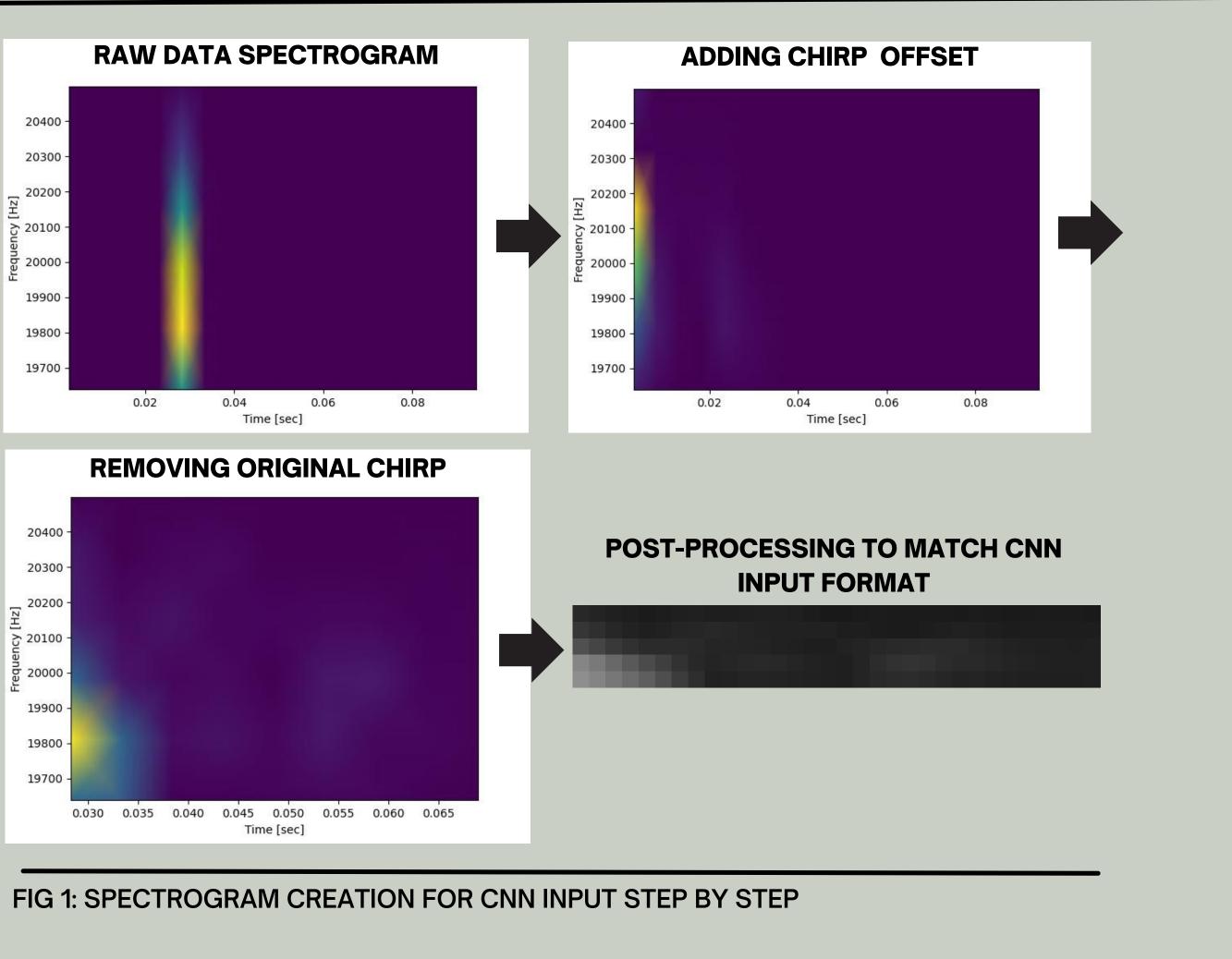
Localization services in mobile app develo outdoor localization precise localization GPS indoors comes that result in accurac recognition. There ar word applications wi localization would pr

# BACKGROUND

RESEARCH QUESTION

Since there are possi for an indoor localiza the past years there proposed solutions range of different tec algorithms.

Can the robustness against music contain be improved?



s are widely used opment. While already provides with GPS, using with challenges[1] cy to low for room re however real where indoor rove helpful.	<ul> <li>Use cases:</li> <li>Indoor way-finding</li> <li>Hospital patient localization</li> <li>Automated museum tour guides</li> <li>Smart-building automatization</li> </ul>	F
sible applications ation service over were multiple that make use of a chnologies and	<ul> <li>Multiple classes of solutions:</li> <li>Acoustic, WIFI based, mixed, etc.</li> <li>Infrastructure-free / Infrastructure-dependant</li> <li>Passive sensing[2] / Active sensing[3]</li> </ul>	0 Irne lapel 2 -
s of the system ining environment	Sub-questions: • How is the system affected by the presence of music in the	3 · N
	<ul> <li>environment?</li> <li>Can deep learning methods be used to improve robustness against music in the environment?</li> </ul>	0 Itre laber 2

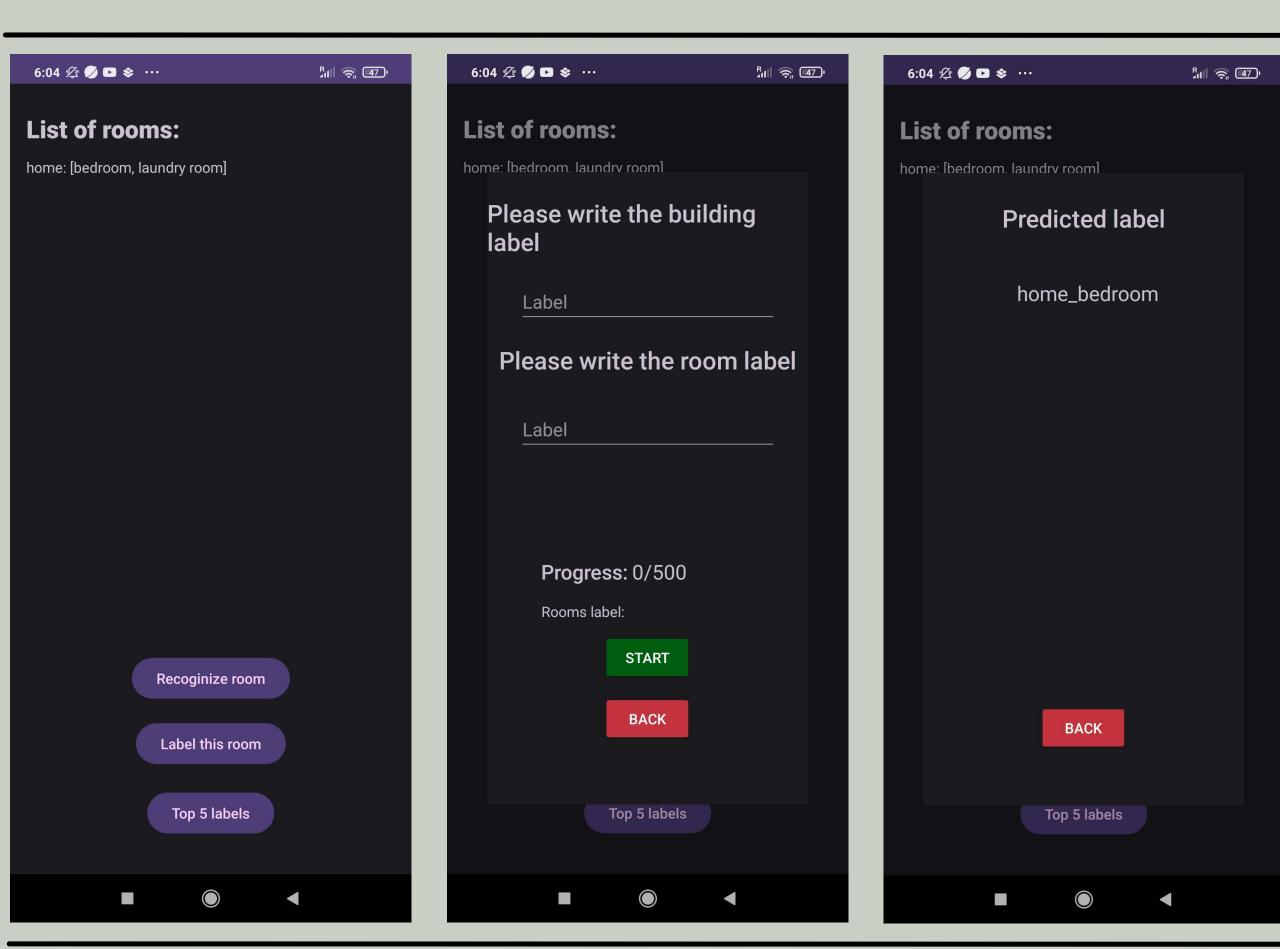
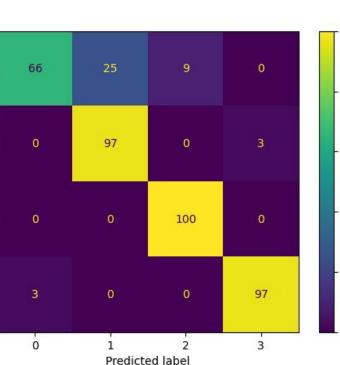


FIG 2: MOBILE APPLICATION DESIGN

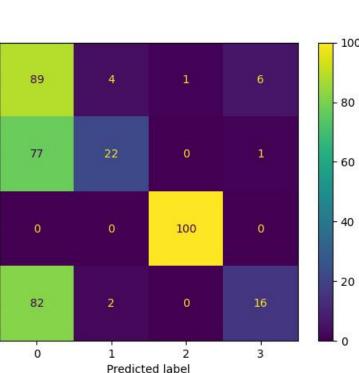
MEAN SPECTROGRAM WITHOUT MUSIC

MEAN SPECTROGRAM WITH MUSIC

**IG 3: MEAN SPECTROGRAMS SHOWING HOW MUSIC IMPACTS THE SYSTEM** 



O MUSIC NO AUTOENCODER



WITH MUSIC NO AUTOENCODER

FIG 4:EXPERIMENT RESULTS

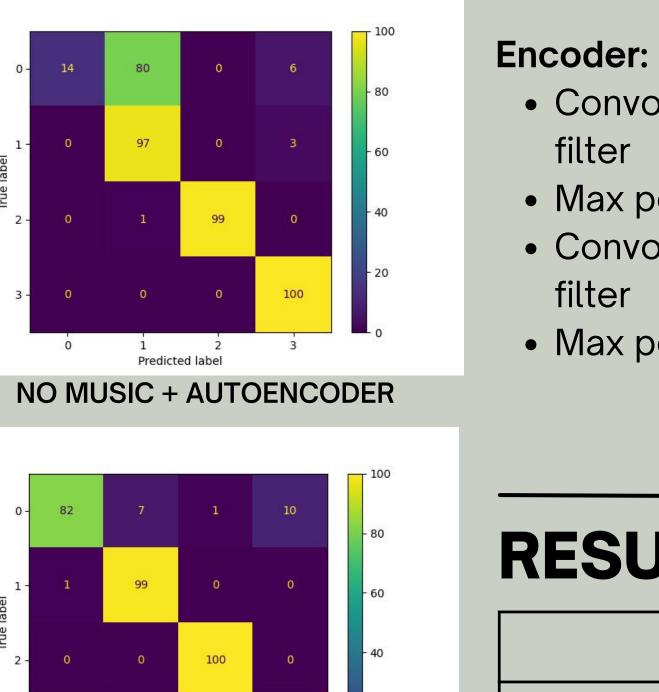
# **METHODOLOGY**

- Implementing proof of concept application Fig 1, 2
- Gathering required datasets
- Evaluating the impact of music on the system Fig 3
- Designing the autoencoder

filter

filter

• Evaluating the performance of the system with and without music ith and without autoencoder



0 1 2 3 Predicted label WITH MUSIC + AUTOENCODER

# RESULTS No music Music Mixed

- Adding the autoencoder introduces a tradeoff between accuracy in music-containing environments and quiet environments - Fig 4
- Accuracy was improved in music-containing environments: Lower accuracy drop • Higher accuracy
- Robustness of the system stayed relatively the same, represented by mixed dataset results

## **REFERENCES:**

[1] G. DEDES AND A.G. DEMPSTER. INDOOR GPS POSITIONING CHALLENGES AND **OPPORTUNITIES. IN VTC-2005-FALL. 2005 IEEE 62ND VEHICULAR TECHNOLOGY CONFERENCE,** 2005., VOLUME 1, PAGES 412–415, 2005

[2] STEPHEN P. TARZIA, PETER A. DINDA, ROBERT P. DICK, AND GOKHAN MEMIK. INDOOR LOCALIZATION WITHOUT INFRASTRUCTURE USING THE ACOUSTIC BACKGROUND SPECTRUM. IN MOBISYS 11: PROCEEDINGS OF THE 9TH INTERNATIONAL CONFERENCE ON MOBILE SYSTEMS, APPLICATIONS, AND SERVICES, PAGES 155–168, 2011.

[3] QUN SONG, CHAOJIE GU, AND RUI TAN. DEEP ROOM RECOGNITION USING INAUDIBLE ECHOS, 2018.

# **TUDelft**

## **AUTOENCODER DESIGN**

• Convolutional layer - 16 5x5

• Max pooling layer - 2x2 filter

Convolutional layer - 16 5x5

### **Decoder**:

- Transposed convolutional layer - 16 5x5 filters
- Transposed convolutional layer - 16 5x5 filters
- Convolutional layer 15x5 filter
- Max pooling layer 2x2 filter

No Autoencoder		With Autoencoder	
Average	std dev	Average	std dev
0.91	0.07	0.81	0.05
0.70	0.10	0.76	0.09
0.81	0.06	0.79	0.04