

# Certificate I: Understanding AI and Machine Learning in Africa

Course AIML02: AI and Machine Learning in Africa

Module 02: Application Case Studies

Lecture 01: Healthcare

**Carnegie Mellon University**  
Africa

# Learning Objectives

1. Explain how AI and machine learning can be used to analyze the cry of a newborn baby and flag the presence of a potential life-threatening condition
2. Identify the stages involved in going from an initial idea to a working application
3. Distinguish the relative strengths and weakness of different AI and machine learning techniques as potential solutions.

# Lecture Contents

1. The birth of an idea
2. Ubenwa: cry-based diagnosis of birth asphyxia
3. Neural transfer learning for cry-based diagnosis of perinatal asphyxia
4. Lecture summary
5. Recommended reading & references

## THE INFANT CRY AS A **VITAL SIGN**

Ubenwa develops AI-powered software for early identification of neurological and respiratory conditions in infants using their cry sounds

Get the app for parents



[www.ubenwa.ai](http://www.ubenwa.ai)

## Mission:

**Leveraging artificial intelligence to create accessible, clinical-grade infant monitoring tools.**

Join the team



[www.ubenwa.ai](http://www.ubenwa.ai)

# The Birth of an Idea

## Charles Onu

- Grew up in Nigeria, wanted to be a doctor, and loved mathematics
- B. Eng. in Electrical Computer Engineering, Federal University of Technology, Owerri
- Started volunteering for Enactus in 2008, where he first learned about **perinatal asphyxia**
- “This is a very big problem for **resource-limited communities in developing countries** like Nigeria where sophisticated detection tools are not available”

## The birth of an idea

Mobile app could save lives by using AI to detect respiratory distress in newborns



Diane Weidner | 7 Jan 2021

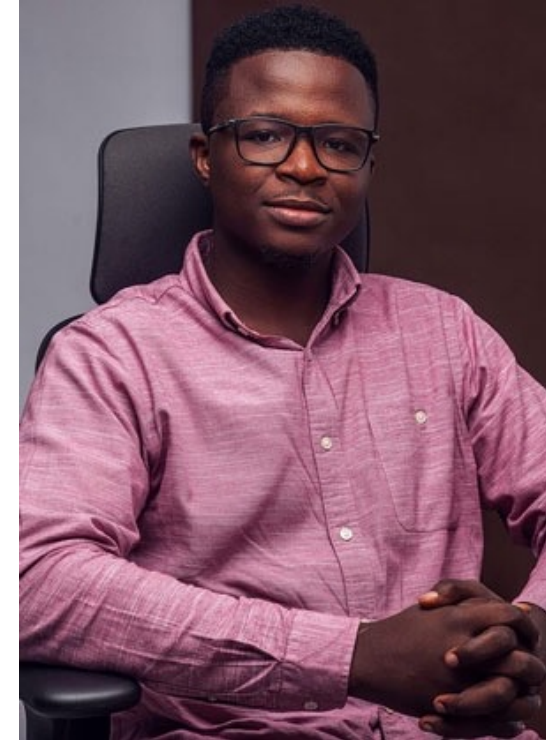
f in [Tweet](#)

<https://www.mcgill.ca/channels/article/birth-idea>

# The Birth of an Idea

## The goal

- Develop a smart tool to identify babies who are showing signs of respiratory distress by **analyzing their cry patterns**
- In 2015, he started working on the problem with **Innocent Udeogu**, a former schoolmate



**Innocent Udeogu**

<https://www.mcgill.ca/channels/article/birth-idea>

# The Birth of an Idea

## Next steps

- Moved to Montreal in 2015 on a Jeanne Sauvé Foundation fellowship as a visiting researcher
- Applied to McGill University and completed a Master's Degree in Computer Science
- Began collaborating with Samatha Latremouille, a graduate from McGill with a B.Sc. in Physiology



# The Birth of an Idea



**Charles C. Onu**  
CEO And AI Lead



**Samantha Latremouille**  
Clinical Development Lead



**Innocent Udeogu**  
Software Engineering Lead

[www.ubenwa.ai](http://www.ubenwa.ai)

# The Birth of an Idea

## Ubenwa

- Cost-effective, non-invasive
- Allows clinicians to flag the risk of newborn asphyxia
- If detected early, it is easy to treat
- Has the potential to save lives of millions of newborns



[www.ubenwa.ai](http://www.ubenwa.ai)

# The Birth of an Idea



[www.ubenwa.ai](http://www.ubenwa.ai)

# The Birth of an Idea

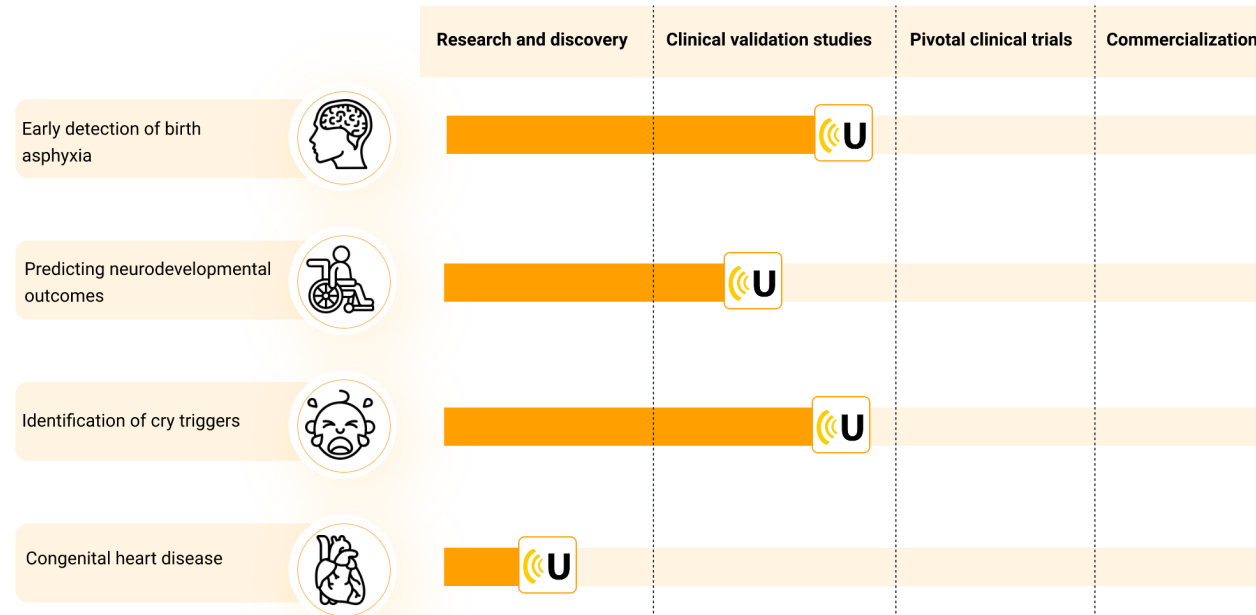


[www.ubenwa.ai](http://www.ubenwa.ai)

# The Birth of an Idea

## Clinical development pipeline

We are developing a robust platform for early screening and monitoring of a range of neurological and respiratory conditions affecting infants.



[www.ubenwa.ai](http://www.ubenwa.ai)



# The Birth of an Idea



[www.ubenwa.ai](http://www.ubenwa.ai)

# The Birth of an Idea



[www.ubenwa.ai](http://www.ubenwa.ai)

# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

## Motivation

- Every year, 3 million babies die within 28 days of being born
- Birth asphyxia is one of the top 3 causes of newborn mortality globally
- It also results to severe, life-long disabilities in over 1 million infants, annually
  - Cerebral palsy
  - Deafness
  - Intellectual difficulty

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## Ubenwa: Cry-based Diagnosis of Birth Asphyxia

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Charles C. Onu<sup>1,2</sup>, Innocent Udeogu<sup>2</sup>, Eyenimi Ndiomu<sup>2</sup>, Urbain Kengni<sup>2</sup>, Doina Precup<sup>1</sup>,  
Guilherme M. Sant'anna<sup>3</sup>, Edward Alikor<sup>4</sup> and Peace Opara<sup>4</sup>\*

### Abstract

Every year, 3 million newborns die within the first month of life. Birth asphyxia and other breathing-related conditions are a leading cause of mortality during the neonatal phase. Current diagnostic methods are too sophisticated in terms of equipment, required expertise, and general logistics. Consequently, early detection of asphyxia in newborns is very difficult in many parts of the world, especially in resource-poor settings. We are developing a machine learning system, dubbed Ubenwa, which enables diagnosis of asphyxia through automated analysis of the infant cry. Deployed via smartphone and wearable technology, Ubenwa will drastically reduce the time, cost and skill required to make accurate and potentially life-saving diagnoses.


(Ona et al., 2017)



# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

## Motivation

Clinical diagnosis of asphyxia involves analysis of an arterial blood sample of the infant to measure blood gases, pH, oxygen saturation and electrolytes, using a blood gas analyser



- Early detection can prevent this
- But hospitals in many developing countries do not have the required equipment
  - Breathing conditions such as asphyxia are generally detected only when the visual symptoms have appeared
  - Severe neurological damage may have already occurred

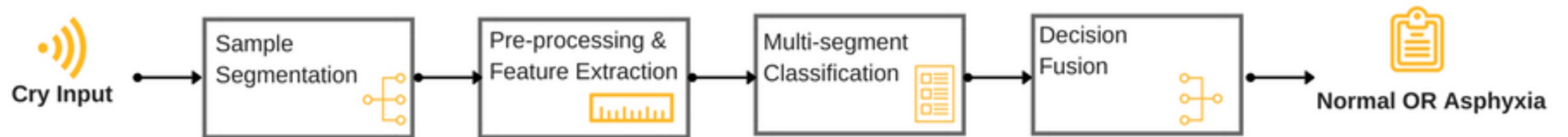
# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

## Motivation

- Develop a diagnostic method for birth asphyxia that allows early detection
  - Inexpensive
  - Easy to use
- Accessible by community health workers, midwives, nurses in developing regions

# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

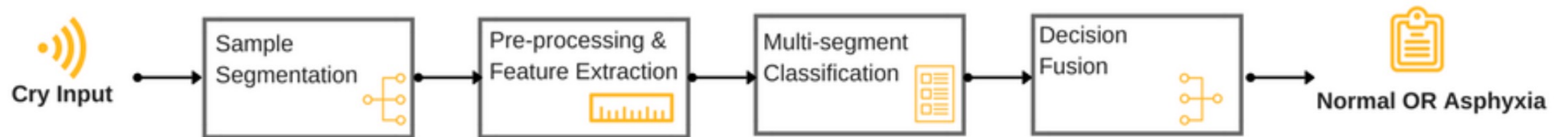
Mel Frequency Cepstral Coefficients (MFCC) with Support Vector Machines (SVM)



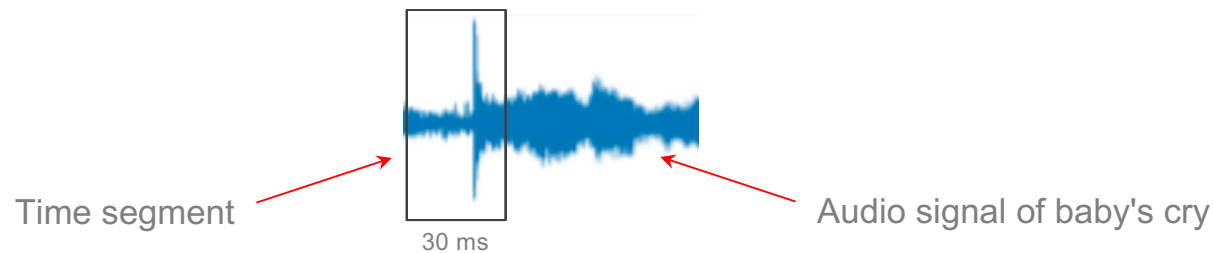
(Ona et al., 2017)

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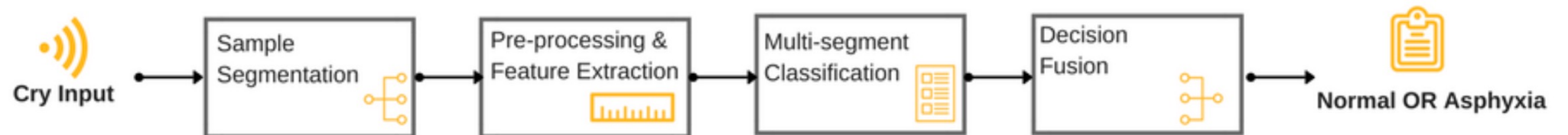


(Ona et al., 2017)

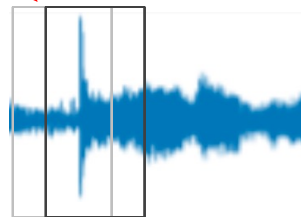


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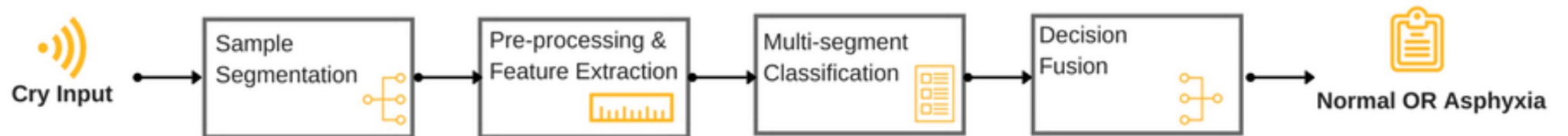
10 ms shift



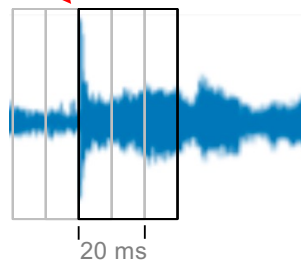
(Ona et al., 2017)

# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

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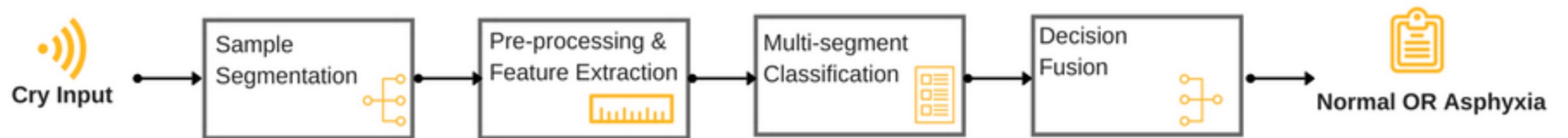
10 ms shift



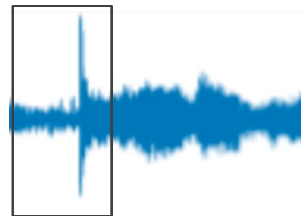
(Ona et al., 2017)

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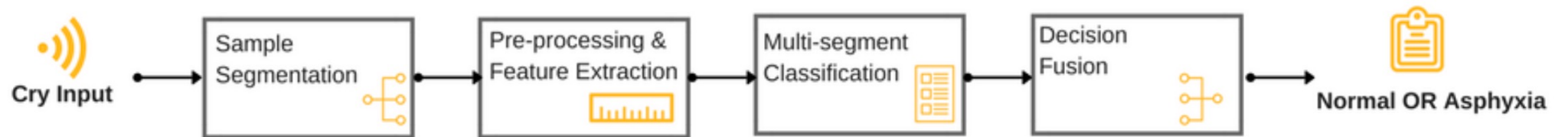


(Ona et al., 2017)

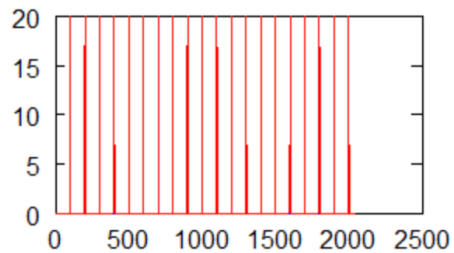


# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

Mel Frequency Cepstral Coefficients (MFCC) with Support Vector Machines (SVM)



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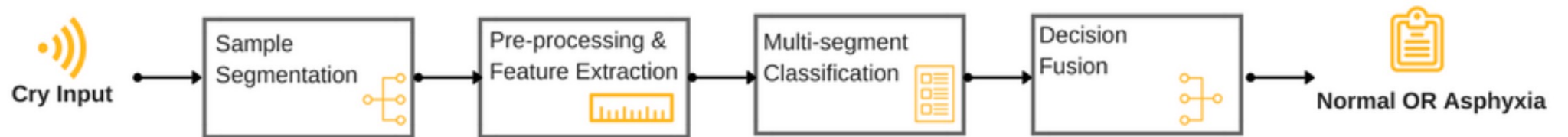


<https://en.wikipedia.org/wiki/Cepstrum>

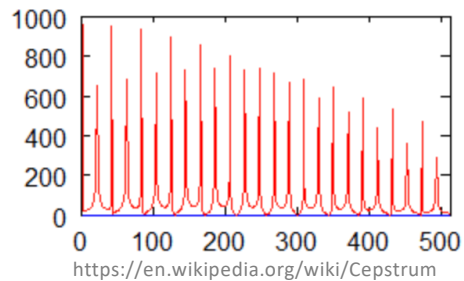


# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

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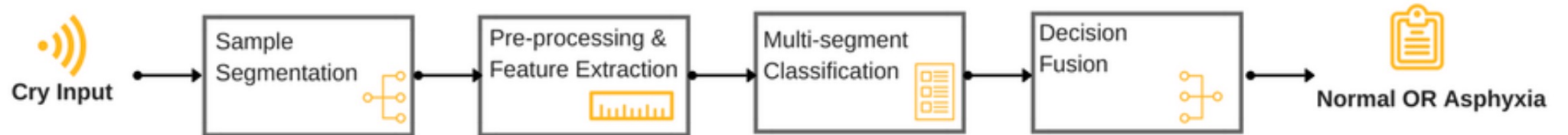
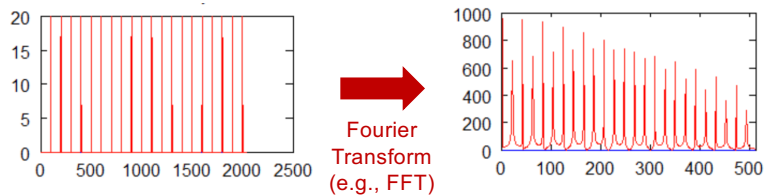


(Ona et al., 2017)

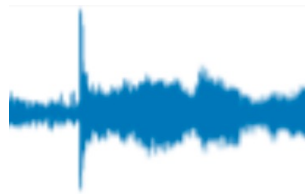


# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

## Mel Frequency Cepstral Coefficients (MFCC) with Support Vector Machines (SVM)

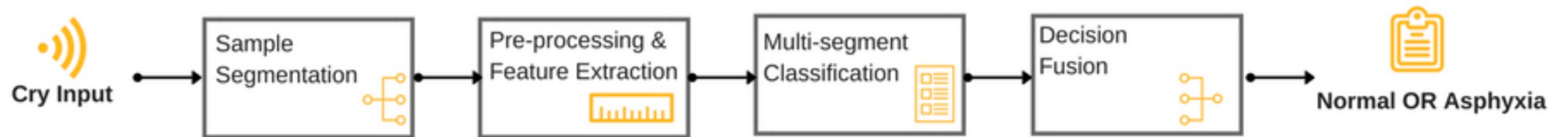
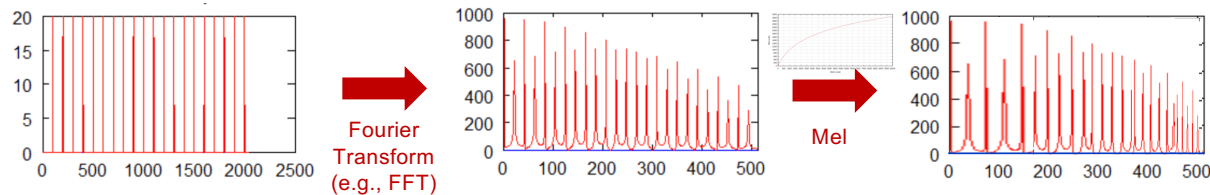


(Ona et al., 2017)



# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

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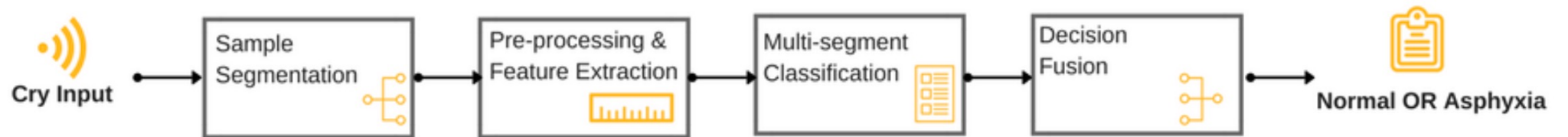
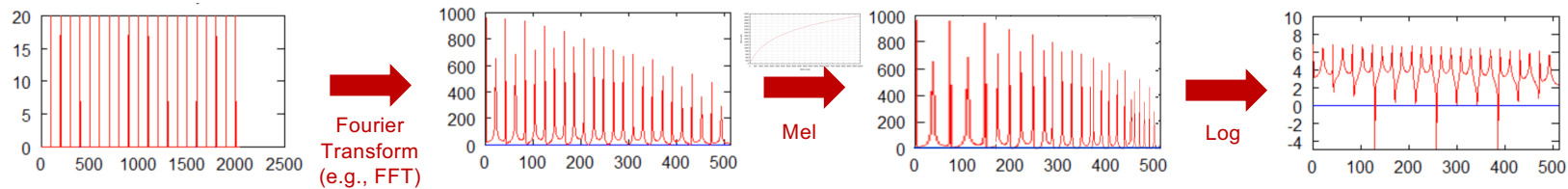


(Ona et al., 2017)

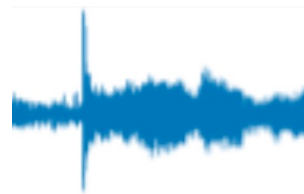


# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

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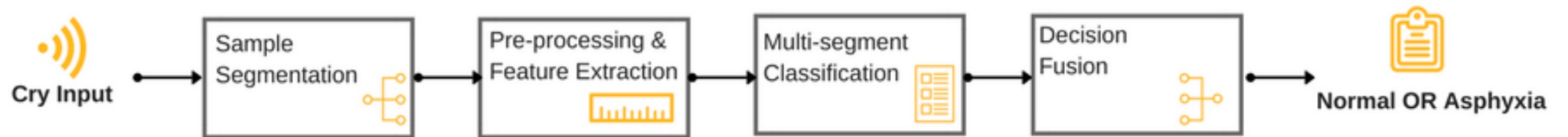
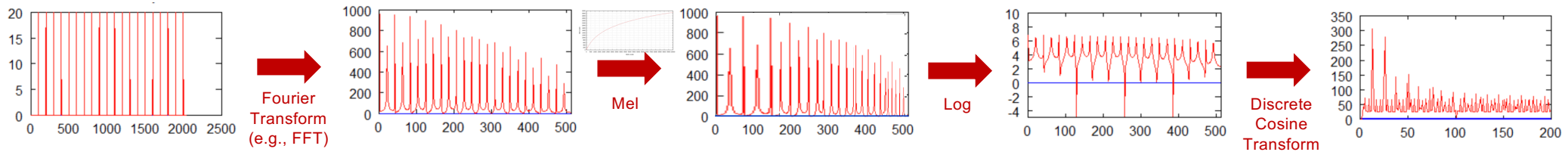


(Ona et al., 2017)



# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

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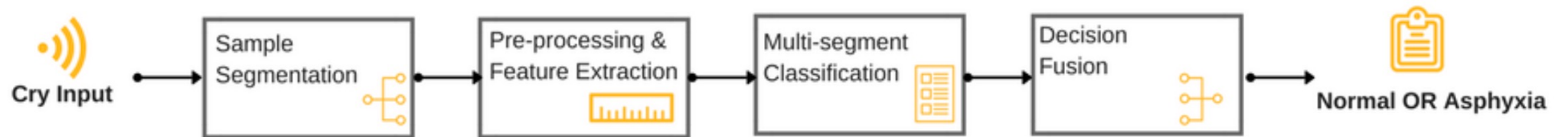
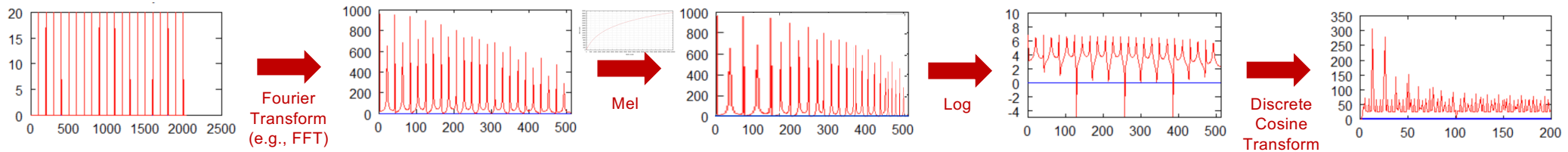


(Ona et al., 2017)

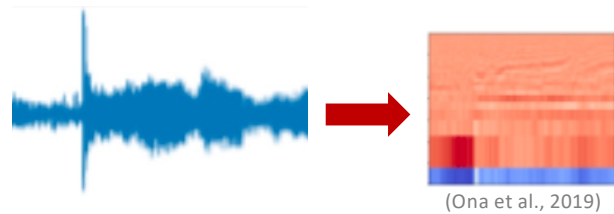


# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

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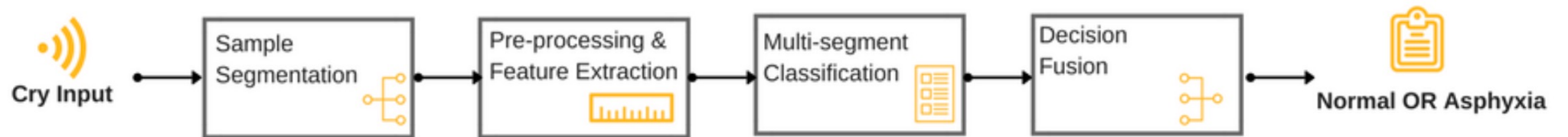
(Ona et al., 2017)



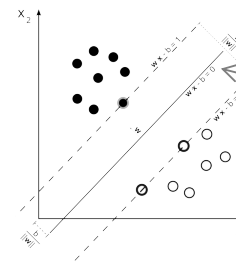
40 MFCCs x 101 columns (one per frame)

# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

Mel Frequency Cepstral Coefficients (MFCC) with Support Vector Machines (SVM)



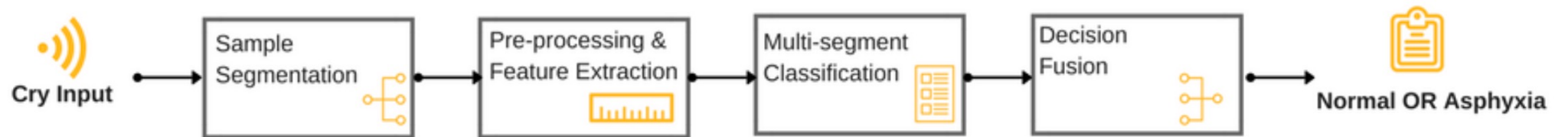
(Ona et al., 2017)



A **Support Vector Machine (SVM)** learns the linear boundary that best separates the two classes; See AIML01, Module 2, Lecture 3, and AIML05

# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

Mel Frequency Cepstral Coefficients (MFCC) with Support Vector Machines (SVM)



(Ona et al., 2017)

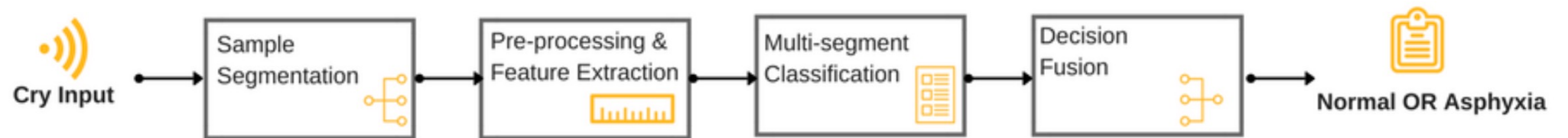
Training the SVM

1389 samples of normal and asphyxiating cries:  
80% was used to train the classifier  
20% for the test set



# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

Mel Frequency Cepstral Coefficients (MFCC) with Support Vector Machines (SVM)

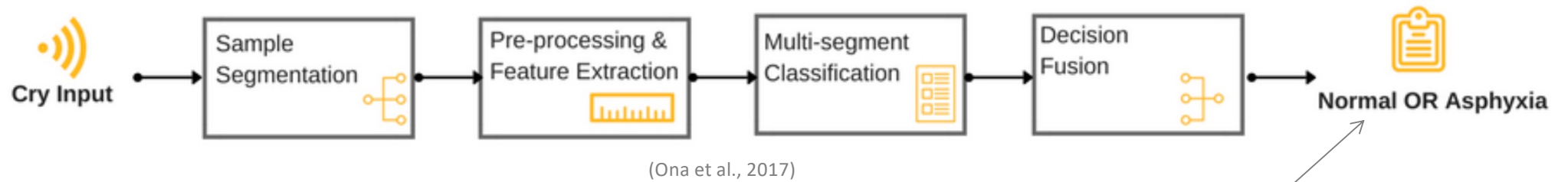


(Ona et al., 2017)

A cry is classified *asphyxia* if the majority of the frames (i.e. segments) were classified as *asphyxia*

# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

Mel Frequency Cepstral Coefficients (MFCC) with Support Vector Machines (SVM)



**Results**

**Sensitivity**

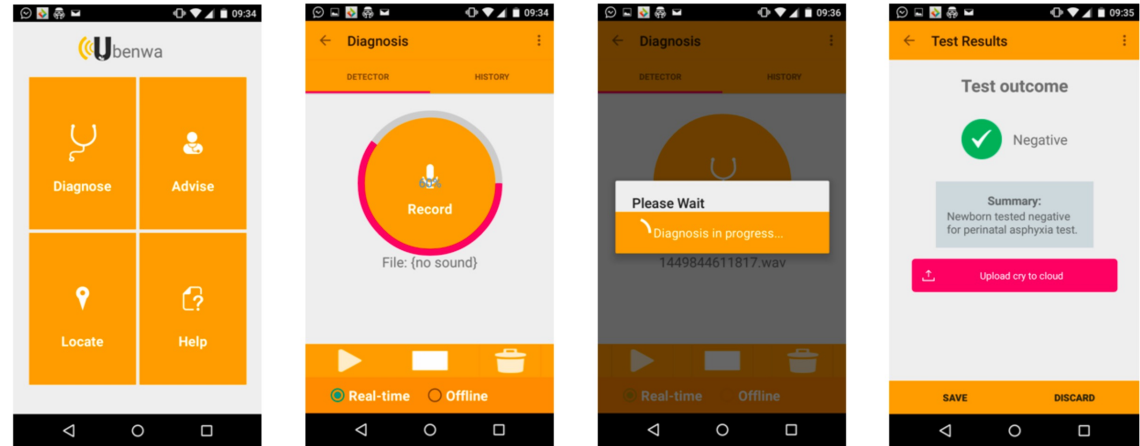
Accuracy in detecting asphyxiating infants: **85%**

**Specificity**

Accuracy in detecting normal infants: **89%**

# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

- Machine learning is only a part of the solution
- It needs to be deployed: here as a mobile application, Ubenwa
- Validation is planned at
  - University of Port Harcourt Teaching Hospital (UPTH), Port Harcourt, Nigeria
  - McGill University Health Centre (MUHC), Montreal, Canada



(Ona et al., 2017)

# Ubenwa: Cry-based Diagnosis of Birth Asphyxia

## Future Enhancements




- Robustness to noise
- Minimizing length of audio recording
- Optimizing memory and computational requirements
- Investigate alternative machine learning techniques

Recurrent neural network (RNN) based models,  
e.g., Long short-term memory (LSTM) model

We first mentioned these approaches in AIML01,  
Module 2, Lecture 3, and AIML11

# Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia

## Comparison of SVM approach with transfer learning using convolutional neural networks

- Transfer learning  Mentioned in AIML01, Module 3, Lecture 1: AI Applications in Medicine
  - First train a neural network model using a large general-purpose dataset
  - Then tuning the trained model using a smaller application-specific dataset
- Convolutional neural networks (CNN) 
  - ResNet  Mentioned in AIML01, Module 2, Lecture 2: Connectionist Approaches to AI

INTERSPEECH 2019  
September 15–19, 2019, Graz, Austria



### Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia

Charles C. Onu<sup>1,2</sup>, Jonathan Lebensold<sup>1,2</sup>, William L. Hamilton<sup>1,3</sup>, Doina Precup<sup>1,4</sup>

<sup>1</sup>Mila - Québec Artificial Intelligence Institute, McGill University

<sup>2</sup>Ubenwa Intelligence Solutions Inc

<sup>3</sup>Facebook AI Research

<sup>4</sup>Google DeepMind

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#### Abstract

Despite continuing medical advances, the rate of newborn morbidity and mortality globally remains high, with over 6 million casualties every year. The prediction of pathologies affecting newborns based on their cry is thus of significant clinical interest, as it would facilitate the development of accessible, low-cost diagnostic tools. However, the inadequacy of clinically annotated datasets of infant cries limits progress on this task. This study explores a neural transfer learning approach to developing accurate and robust models for identifying infants that have suffered from perinatal asphyxia. In particular, we explore the hypothesis that representations learned from adult speech could inform and improve performance of models developed on infant speech. Our experiments show that models based on such representation transfer are resilient to different types and degrees of noise, as well as to signal loss in time and frequency domains.

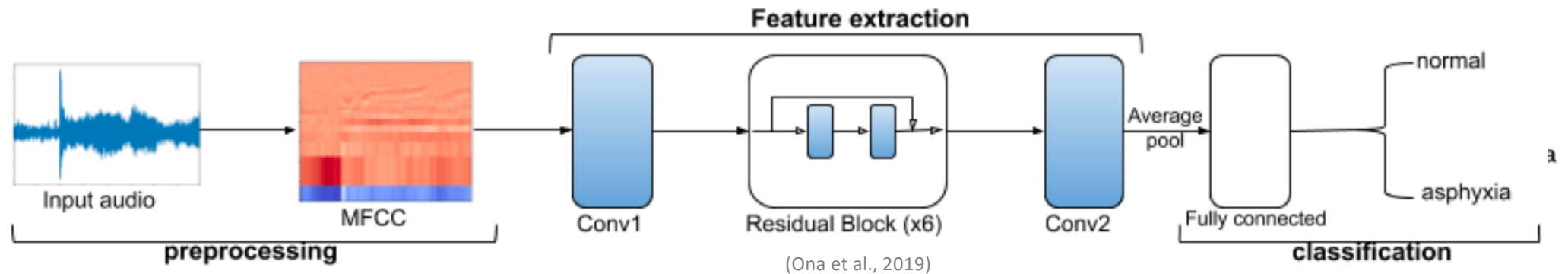
the environment. We nevertheless explore the hypothesis that there exists some underlying similarity in the mechanism of the vocal tract between adults and infants, and that model parameters learned from adult speech could serve as better initialization (than random) for training models on infant speech.

Of course, the choice of source task matters. The task on which the model is pre-trained should capture variations that are relevant to those in the target task. For instance, a model pre-trained on a speaker identification task would likely learn embeddings that identify individuals, whereas a word recognition model would likely discover an embedding space that characterizes the content of utterances. What kind of embedding space would transfer well to diagnosing perinatal asphyxia is not clear a priori. For this reason, we evaluate and compare 3 different (source) tasks on adult speech: speaker identification, gender classification and word recognition. We study how different

(Ona et al., 2019)

# Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia

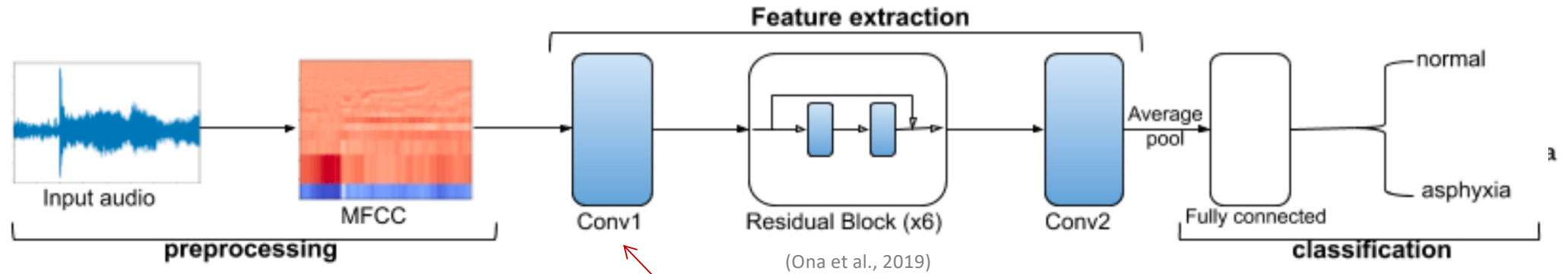
Mel Frequency Cepstral Coefficients (MFCC) with ResNet and Transfer Learning



Same as the SVM approach

# Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia

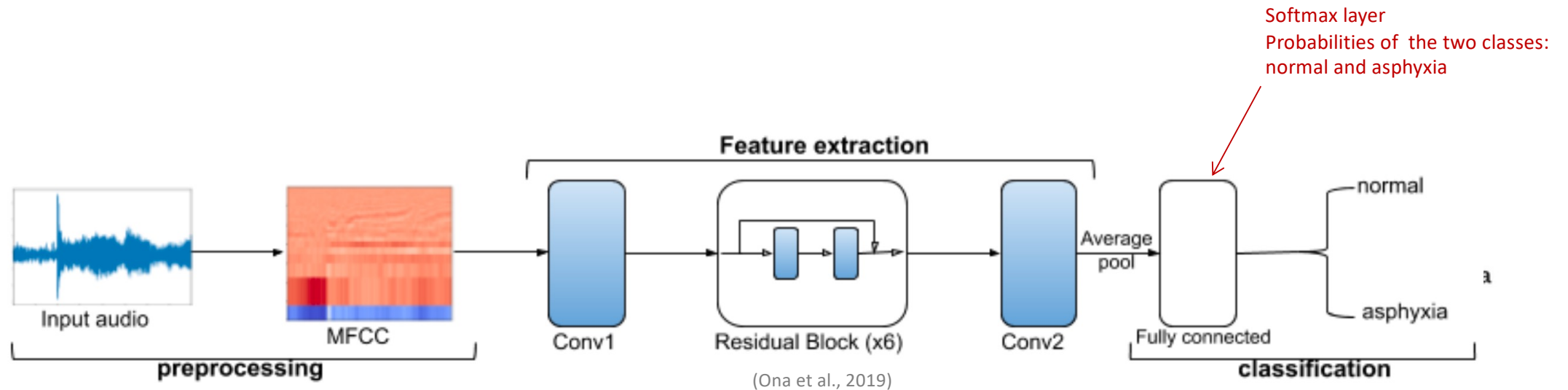
Mel Frequency Cepstral Coefficients (MFCC) with ResNet and Transfer Learning



Each convolution layer has 45 3x3 kernels, i.e., the network learns 45 individual features

# Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia

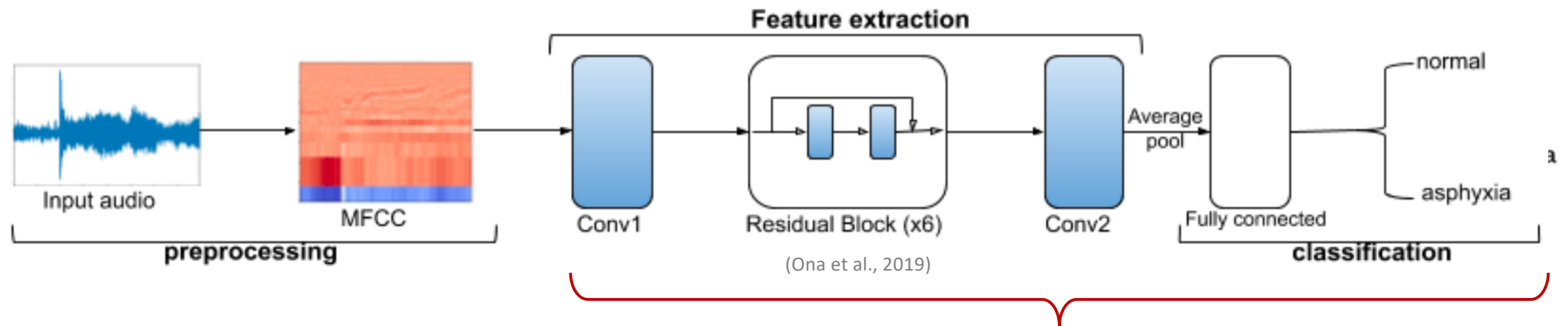
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# Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia

Mel Frequency Cepstral Coefficients (MFCC) with ResNet and Transfer Learning

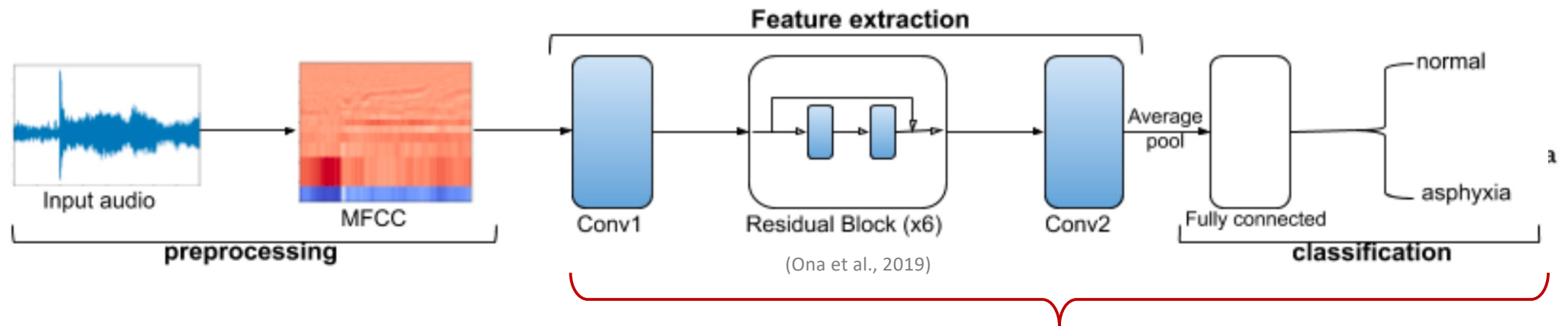


ResNet CNN pre-trained on three audio data sets

1. VCTK
2. Speakers in the Wild (SITW)
3. Speech Commands (SC)

# Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia


Mel Frequency Cepstral Coefficients (MFCC) with ResNet and Transfer Learning



For each case, ResNet was then post-trained on the Chillanto dataset:  
1049 recordings of normal infants and 340 recordings of infants with perinatal asphyxia

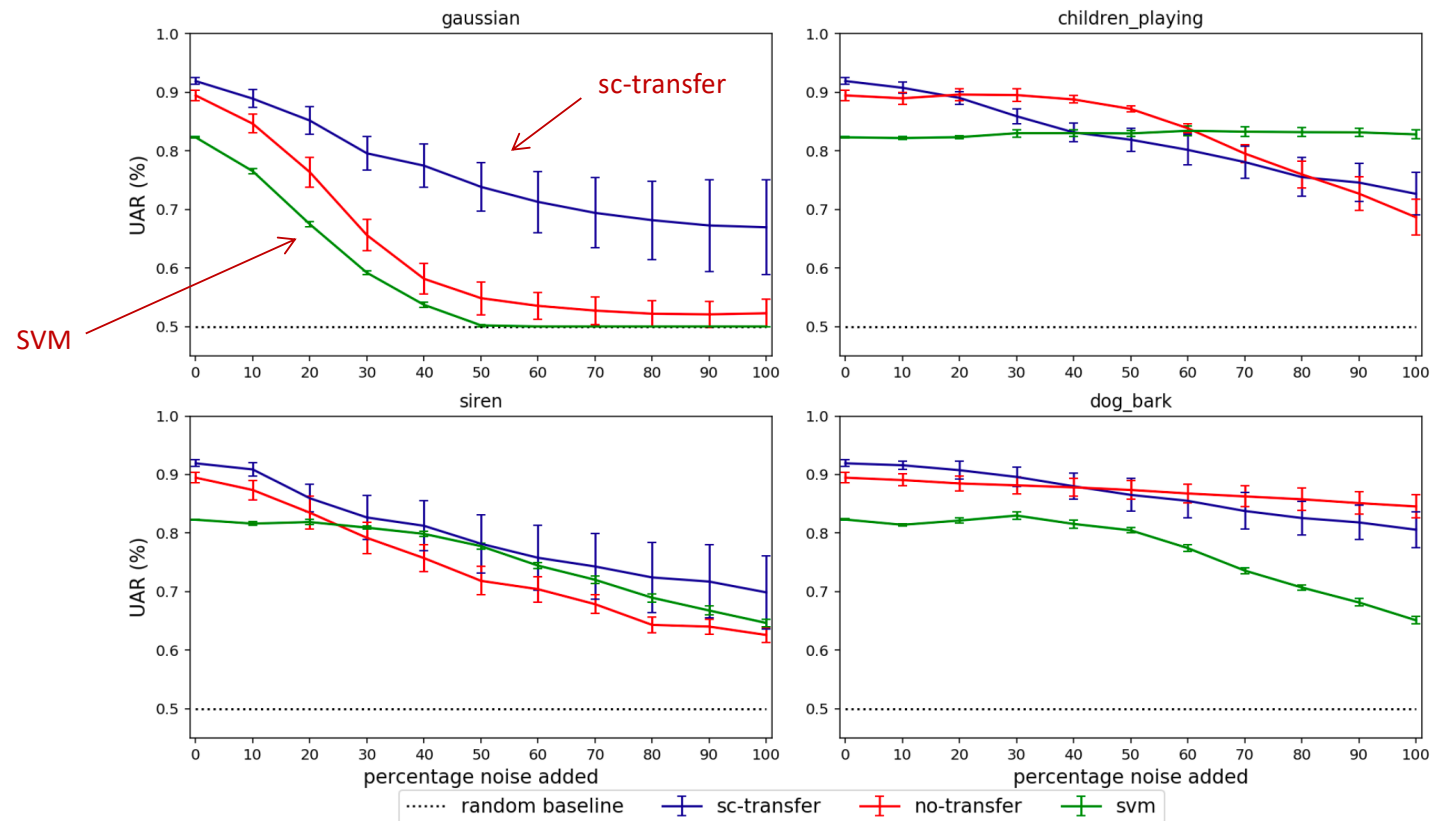
# Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia

- The results show that the **best performance was achieved by transfer learning with the speech commands (SC) data set**
- SVM was the second-best performing model

Model	UAR %	Sensitivity %	Specificity %
SVM	84.4 (0.4)	81.6 (0.7)	87.2 (0.2)
no-transfer	80.0 (2.5)	71.8 (5.8)	88.1 (0.8)
 sc-transfer	<b>86.5 (1.1)</b>	<b>84.1 (2.2)</b>	<b>88.9 (0.4)</b>
sitw-transfer	81.1 (1.7)	72.7 (3.5)	89.5 (0.2)
vctk-transfer	80.7 (1.0)	72.2 (2.1)	89.1 (0.3)

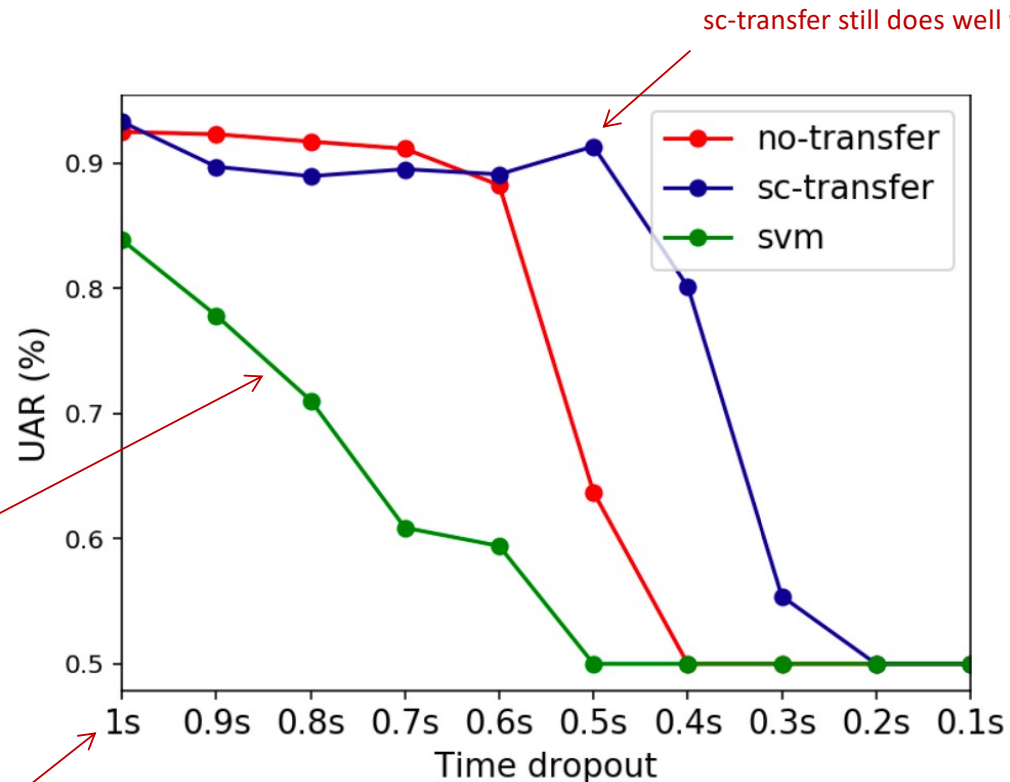
(Ona et al., 2019)

# Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia



(Ona et al., 2019)

# Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia



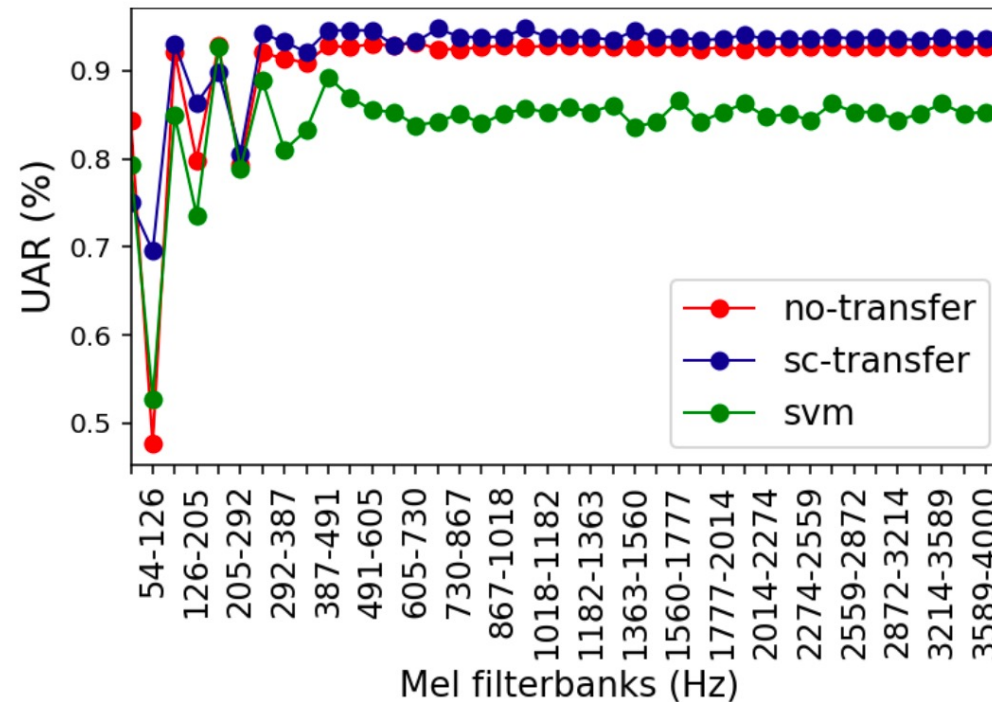
sc-transfer still does well with 0.5 s recordings

The performance of SVM decreases steadily as the duration decreases

The length of the recording decreases from left to right  
The performance for the full 1 s recording is on the left

(Ona et al., 2019)

# Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia



(Ona et al., 2019)

# Lecture Summary

1. A **baby's cry** can be used as input for **diagnosis of asphyxia** with significant economic, social, and clinical benefits
2. Diagnosis can be performed using techniques based on a **support vector machine** supervised machine learning, using mel-frequency cepstral coefficients derived from the baby's cry as the **feature vector**
3. Performance with a ResNet deep neural network and transfer learning is slightly better
4. Ubenwa is **non-invasive**, **low-cost**, requires **little or no skill** to operate, and **delivers results quickly**

# Recommended Reading

Onu, C. C., Udeogu, I., Ndiomu, E., Kengni, U., Precup, D., Sant'anna, G. M., Alikor, E. A. D., and Opara, P. (2017) Ubenwa: Cry-based Diagnosis of Birth Asphyxia, Machine Learning for Development Workshop, 31st Conference on Neural Information Processing Systems.  
<https://arxiv.org/pdf/1711.06405.pdf>

Onu, C. C., Lebensold, J., Hamilton, W. L., and Precup, D. (2019). Neural Transfer Learning for Cry-based Diagnosis of Perinatal Asphyxia, 20th Annual Conference of the International Speech Communication Association INTERSPEECH, pp. 3053–3057.  
[https://www.isca-speech.org/archive/pdfs/interspeech\\_2019/onu19\\_interspeech.pdf](https://www.isca-speech.org/archive/pdfs/interspeech_2019/onu19_interspeech.pdf)

Weidner, D. The Birth of an Idea (2021)  
<https://www.mcgill.ca/channels/article/birth-idea>



# References

Tang, R. and Lin, J. (2018). Deep Residual Learning for Small-footprint Keyword Spotting,  
<https://arxiv.org/pdf/1710.10361.pdf>