#### A Low Power and Small Area Analog Voice Activity Detector Featuring a Time-Domain CNN as a Programmable Feature Extractor and a Sparsity-Aware Computational Scheme in 28nm CMOS

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## Outline

#### Motivation and Prior Arts

#### Proposed Analog Voice Activity Detector (VAD)

- Time-Domain Convolutional Neural Network (TD-CNN)
- Sparsity-Aware Computation (SAC)
- Sparsified Quantization (SQ)
- Measurement Results

#### Conclusions

# **Edge Computing VAD**



Speech recognition(SR) for smart assistant, automatic subtitle, etc.

- Always on VAD activates SR when there is human voice
- Edge computation for privacy and reducing system power

# Analog Feature Extractor (AFE) + Decision Tree (DT)-based Classifier



# DT: inferior to Neural Network (NN)-based classifier AFE: power and area consuming

## **AFE + BNN Classifier**



[M. Yang, et al. ISSCC'18]



#### **X** AFE: power and area consuming $\square$ BNN classifier **X** Require high resolution ripple counter $\rightarrow$ High Power

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## **Mixer-based AFE + NN Classifier**



#### Mixer-based TI-AFE: ☑ Power ☑ Area 🗵 Latency (512ms) ☑ Incomplete extracted feature

## **Proposed VAD**



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# **System Architecture of VAD**



Sampling capacitor array as analog memory
Switched capacitor-based TD-CNN as feature extractor

# System Architecture of VAD



Binarized features processed by BNN for VAD O/P
Sensitivity threshold control to balance FP and FN

# **Time Domain-CNN - Overview**



# Analog voltage is extracted as binary feature maps TD-CNN includes analog memory and convolution

# **TD-CNN – Sampling Cycle**



# **TD-CNN – Computing Cycle**



60 kernels evaluated temporally in the 80<sup>th</sup> sample

#### MAC output is 1-bit quantized for further classification

# **Sparsity-Aware Computation (SAC)**



Top-plate sampling MAC unit (N=79)
0-weight is open to avoid charge sharing
Increase signal swing of the MAC operation

# **Sparsified Quantization (SQ)**





Compatible to central limit theorem as kernel size is small (N=79)
Test acc. of 3-bit SAC+SQ is higher than 7-bit binary quantization

# **Comparator Offset and Noise**

![](_page_16_Figure_1.jpeg)

VAD more robust to offset and noise with sparsified quantization

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## Chip Photo + Power/Area Breakdown

![](_page_18_Figure_1.jpeg)

### **Measurement Results**

![](_page_19_Figure_1.jpeg)

## **TD-CNN as Feature Extractor of KWS**

![](_page_20_Figure_1.jpeg)

- KWS (2 keywords) consists TD-CNN and a 2D-CNN
- Features extracted by TD-CNN are concatenated for the classifier
- 2 TD-CNNs in parallel to increase feature size for better accuracy

## **Comparison – Feature Extractor**

Feature Extractor	This Work	ISSCC'19 [4]	ISSCC'18 [2]	ISSCC'15 [3]
Feature Extraction Topology	TD-CNN Feature Extraction	Time-Interleaved- Mixer-based Frequency Ext.	Analog-to-Event Filter Bank	Analog Filter Bank
Programmable Feature Extractor	Yes (TD-CNN + Sparsity SC)	Yes (b-DCT Sequence)	No	No
Channel Number	60 🗸	16-48	16	16
Frequency Range (Hz)	100 to 4k	75 to 4k	100 to 5k	75 to 5k
Feature Type	<b>Binary Adaptive</b>	Digital Frequency	Event-based Frequency	Analog Frequency
Power Consumption (nW)	73* 🗸	60	380	6000
Area (mm <sup>2</sup> )	0.055 🗸	0.56	1.6	2.56

\* power consumed by the clock buffers for the sampling, charge-sharing buffers and LNA

## **Comparison – Voice Activity Detector**

Voice Activity Detector	This Work		ISSCC'19 [4]	ISSCC'18 [2]	ISSCC'17 [1]	JSSC'21[5]
Classifier	TD-CNN + BNN		Neural Network	BNN	Digital Fixed-Point Deep Neural Network	Analog SNR Decision Rule
Classification Rate (Hz)	100 🗸		2	100	100	31.25
Dataset	TIMIT + NOISEX-	92	LibiSpeech + NOISEX-92	AURORA4 + DEMAND	AURORA2	Custom
Accuracy (SP HR/Non-SP HR)	90.1%/94% @ 10dB SNR		91.5%/90% @ 10dB SNR	84%/85% @ 10 dB SNR	90% @ 7 dB SNR	Not Comparable
Power Consumption (nW)	108		142	1000	22300	760
Energy/classification (nJ)	1.08 🗸		73	10	223	24.32
Chip Area (mm²)	0.8 🗸		17.6**	2.5	2.1	0.14 (Active)
Technology	28 nm CMOS		180 nm CMOS	180 nm CMOS	65 nm CMOS	180 nm CMOS

\*\* Area including an audio compressor and a processor

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# A 108nW 0.8mm<sup>2</sup> analog voice activity detector is implemented in 28nm CMOS

TD-CNN as Feature Extractor	Reduce area and power consumption Reduce A/D conversions More reconfigurable
Sparsity-Aware Computation	Increase signal swing of the MAC operation
Sparsified Quantization	Diversify the output to desensitize the output from mismatches and noise

## Acknowledgments

![](_page_25_Picture_1.jpeg)

#### Multi-Year Research Grant of University of Macau

![](_page_25_Picture_3.jpeg)

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