CeADAR
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04/06/2020: Paul Nulty
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Machine Learning for Cybersecurity

18/06/2020: Claudia Mazo Vargas
Medical images analysis and machine learning

25/06/2020: Anthony Faustine
Machine Learning for Electric Power Consumption Data

02/07/2020: Wael Rashwan
Computational Modelling and Simulation for Spreading of Epidemics

09/07/2020: Susan McKeever
Key developments in machine learning

16/07/2020: Robert Ross
Intelligent Conversational Interfaces

23/07/2020: Inder Preet
Hardware for Machine Learning

'making the possible real'

SUPERMARKET

*** SHOPPING BILL ***

Aa	Bb	Cc	Dd	Ee	3.99
Ff	Gg	Hh	Ii	Jj	8.85
Kk	Ll	Mm	Nn	Oo	2.14
Pp	Qq	Rr	Ss	Tt	0.58
Uu	Vv	Ww	Xx	Yy	7.26
Zz	$£	%:	+=	@!	3.07

Total: 25.89

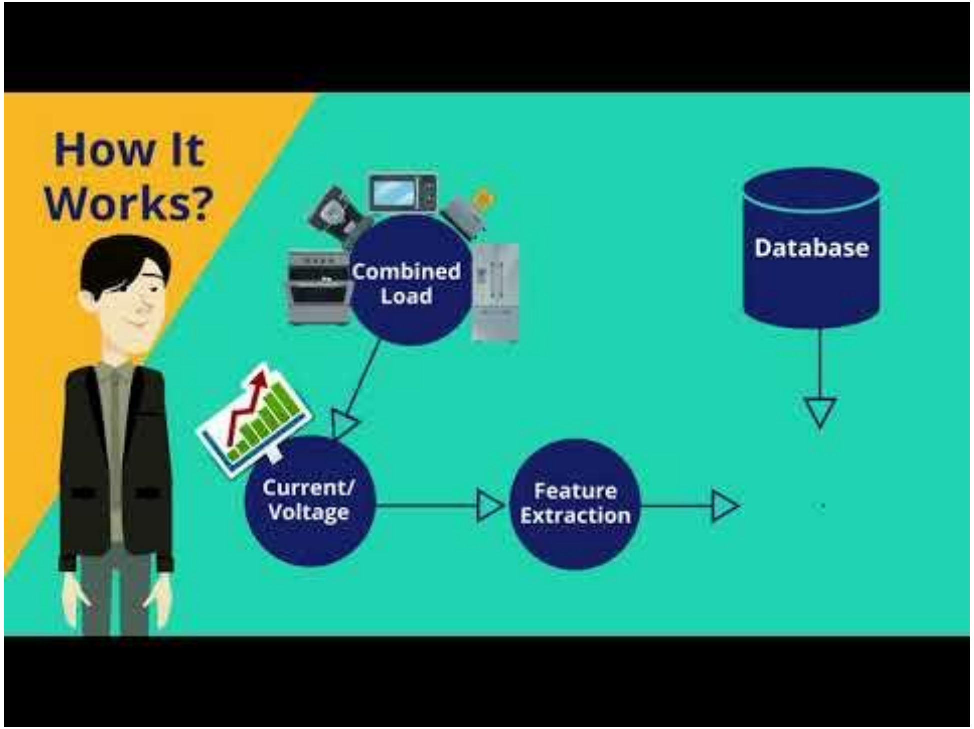
YOUR BILL (FRONT)

Bill Summary		
Your last bill	€200.00	
Payments / Transactions	€200.00 cr	11
Balance Brought Forward	€0.00	12
Charges for this period	€197.84	13
VAT	€26.71	
Total due	**€224.55**	14
Pay by	**Direct Debit**	15

Robust Machine Learning for Appliance Recognition in Non-Intrusive Power Monitoring

Anthony Faustine

What is NILM

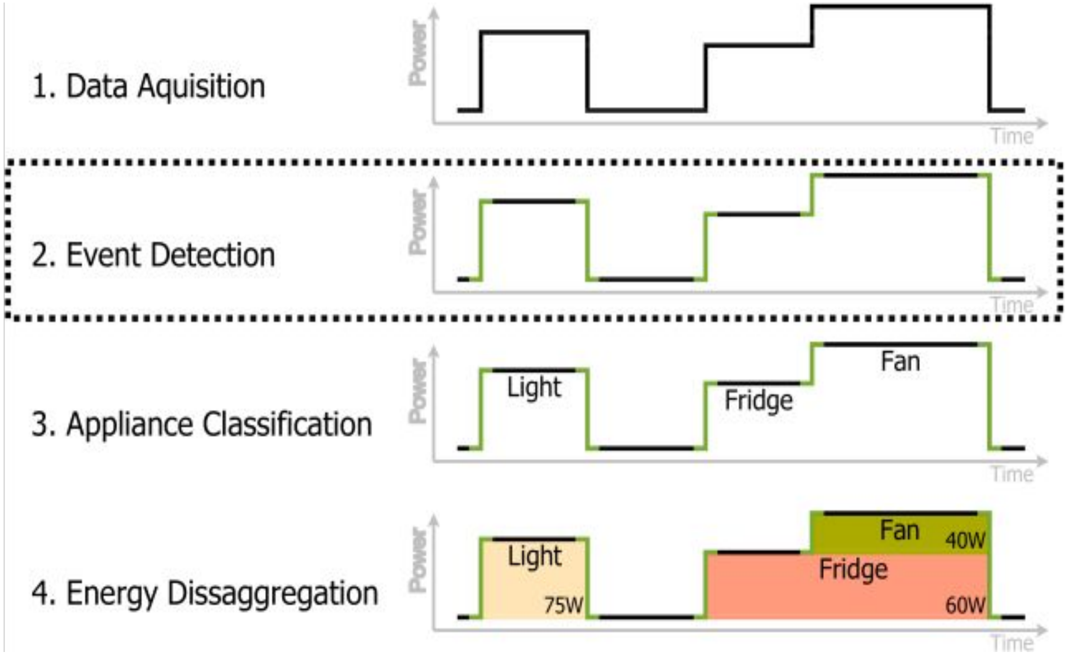

How It Works?
Combined Load
Database
Current/ Voltage
Feature Extraction

NILM: Event vs Non-Event

Figure 1. Typical NILM framework [8].

Event-based	**Non-event based**
• disaggregate appliances by means of detecting and classifying their individual transitions in the aggregated signal. • High frequency • Hybrid approach	• match each sample of the aggregated signal to the consump-ion of one or more appliances • Low frequency • HMM and Deep-learning appraoches

NILM Event based



NILM: Appliance recognition

Identify active appliances from aggregate signal

- A challenging problem in buildings with multiple loads.
- Performance of the existing approaches is yet unsatisfactory.
- Appliance feature (signature) is an important performance factor.

Appliance recognition: V-I Appliance feature

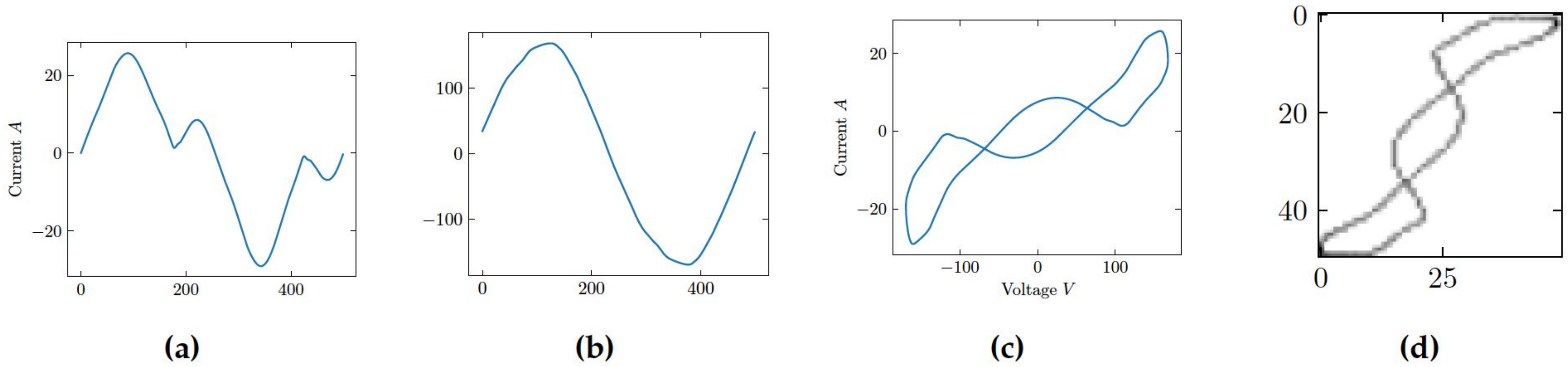
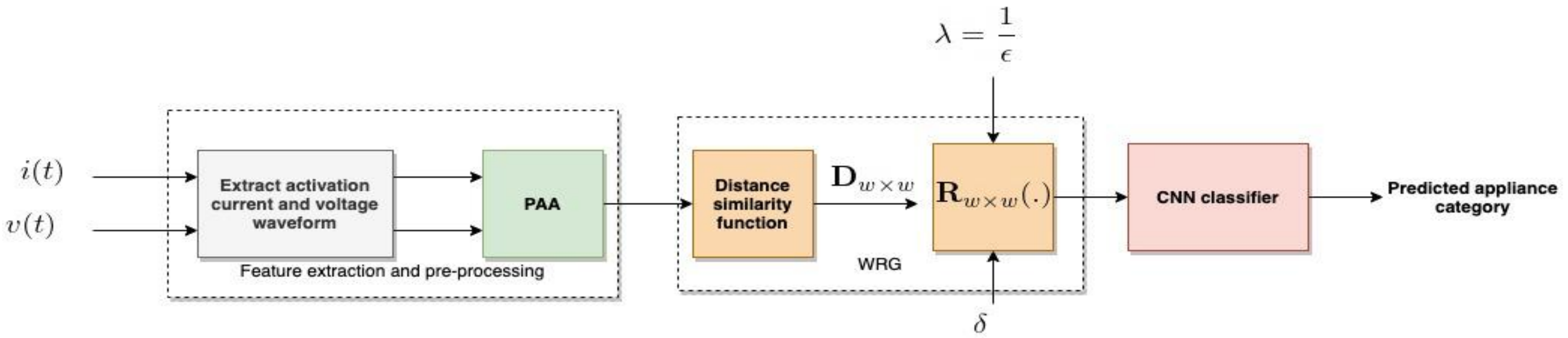


Figure 5. Generation of V-I image from Microwave activation current and voltage in the PLAID dataset (a) Activation current (b) Activation voltage (c) V-I trajectory d) Generated V-I image.

De Baets, L.; Ruyssinck, J.; Develder, C.; Dhaene, T.; Deschrijver, D. ***Appliance classification using V-I trajectories and convolutional neural networks.*** *ENERGY AND BUILDINGS 2018, 158, 32–36.*

Proposed Method-1: Apply compressed distance-similarity matrix



$$r_{k,j} = \begin{cases} \delta & \text{if} \quad \tau > \delta \\ \tau & \text{otherwise} \end{cases}$$

$$\tau = n \leq d_{u,v} \cdot \lambda \leq (n+1), 0 \leq n \leq \delta, \lambda \geq 0$$

Anthony Faustine *, Lucas Pereira, ***Improved Appliance Classification in Non-Intrusive Load Monitoring using Weighted Recurrence Plots and Convolutional Neural Networks***. *Accepted for publication MDPI-Energies Journal*

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Research interest: AI4Sustainability, Deep learning, Statistical Learning