A Machine Hearing Framework for Real-Time Streaming Analytics using Lambda Architecture

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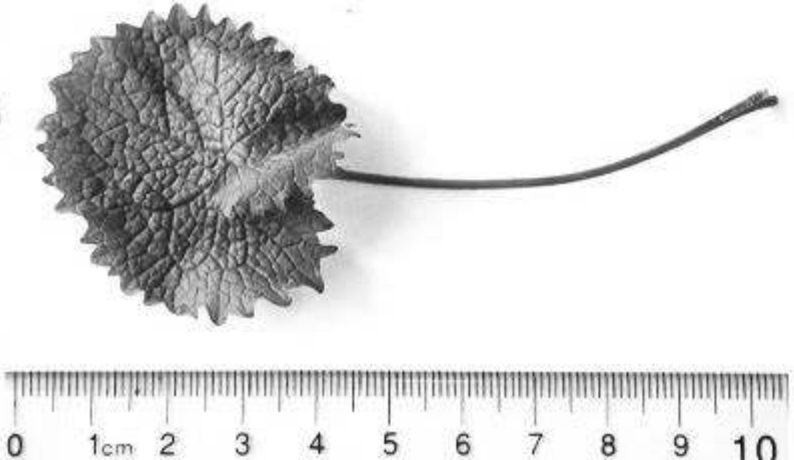
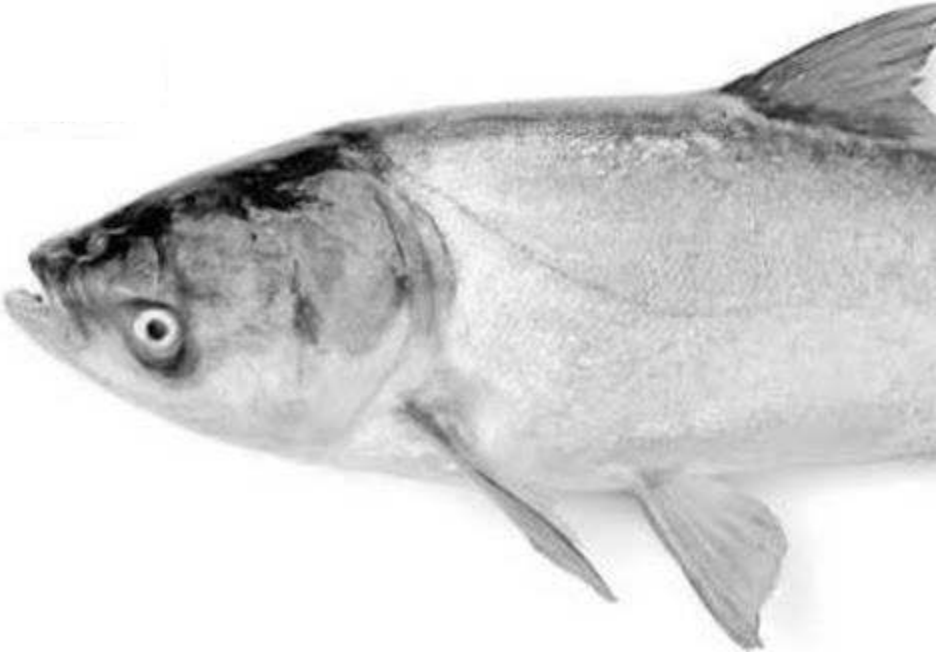
The heat is melting glaciers and sea ice, shifting precipitation patterns, and setting animals on the move.

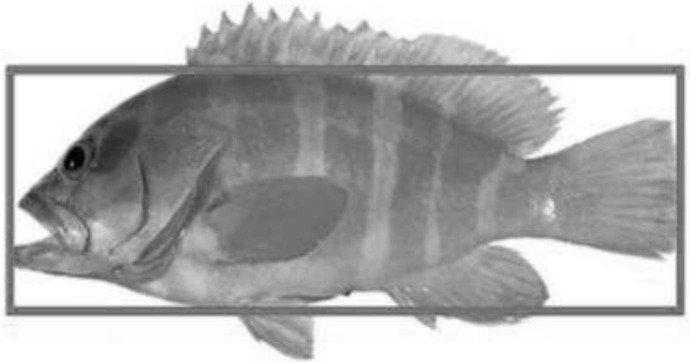
INVASIVE SPECIES



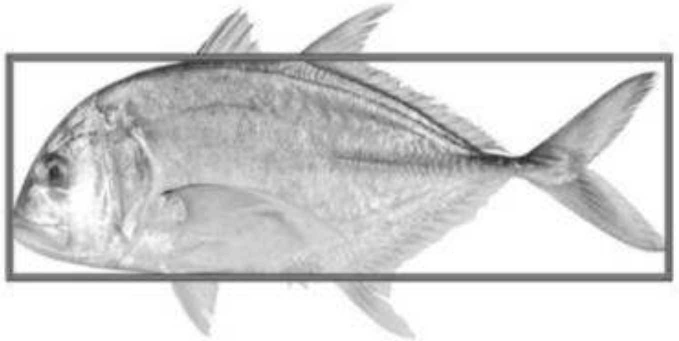


environmentalDNA

DNA BARCODING

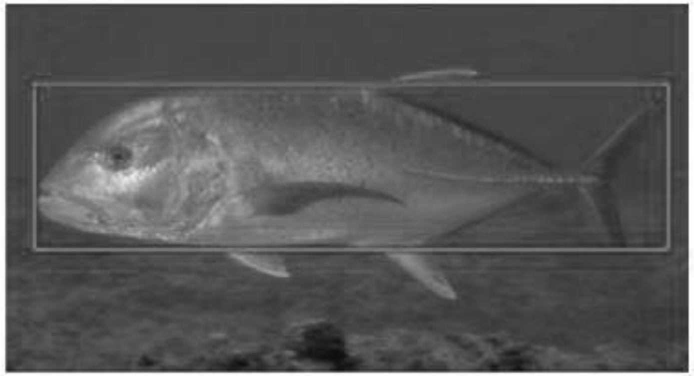


(a) “controlled”



(b) “controlled”

(c) “in-situ”



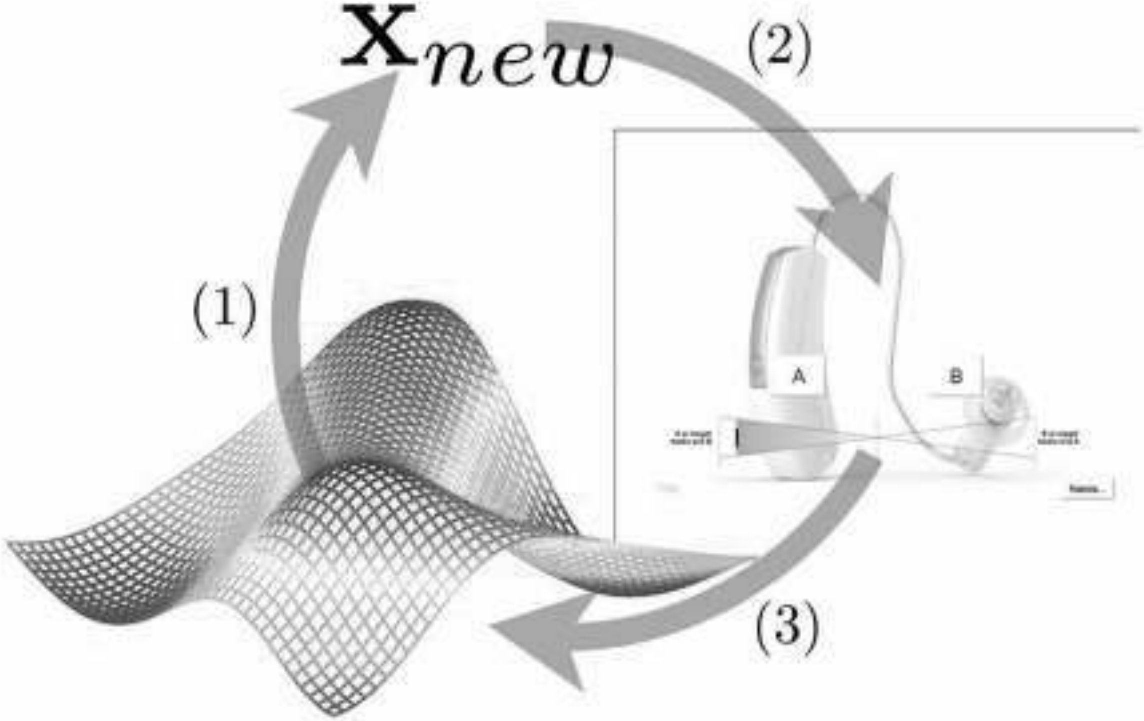
(d) “in-situ”

(e) “out-of-the-water”

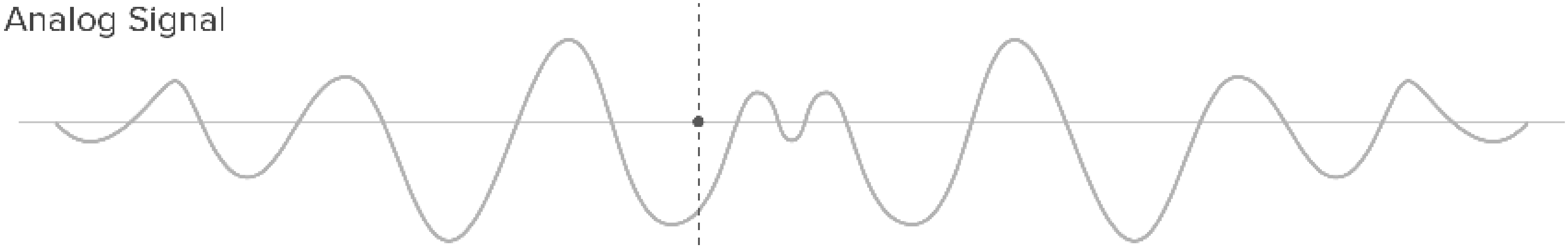
(f) “out-of-the-water”

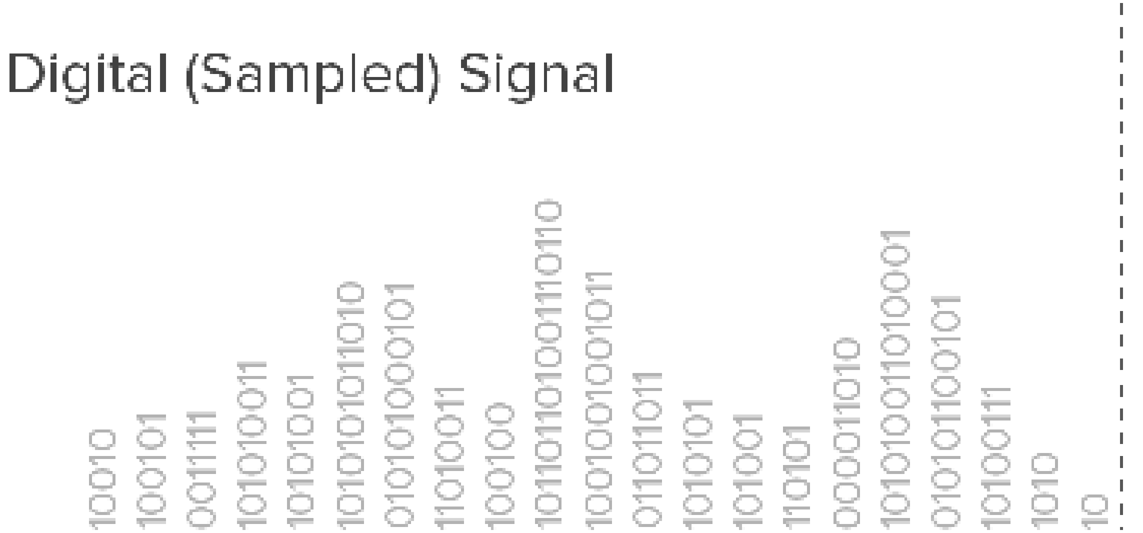

INVASIVE SPECIES

Machine Hearing

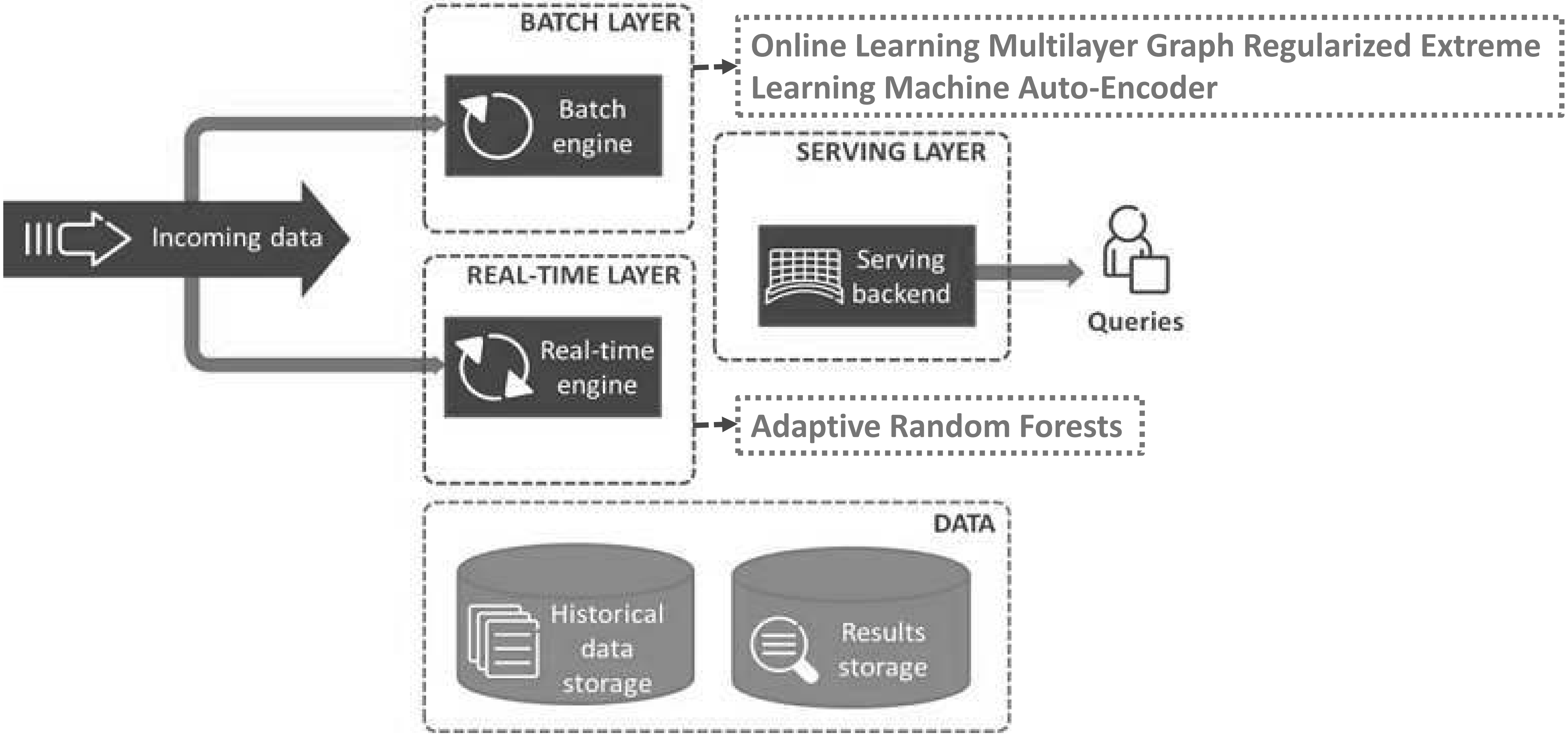


Machine Hearing

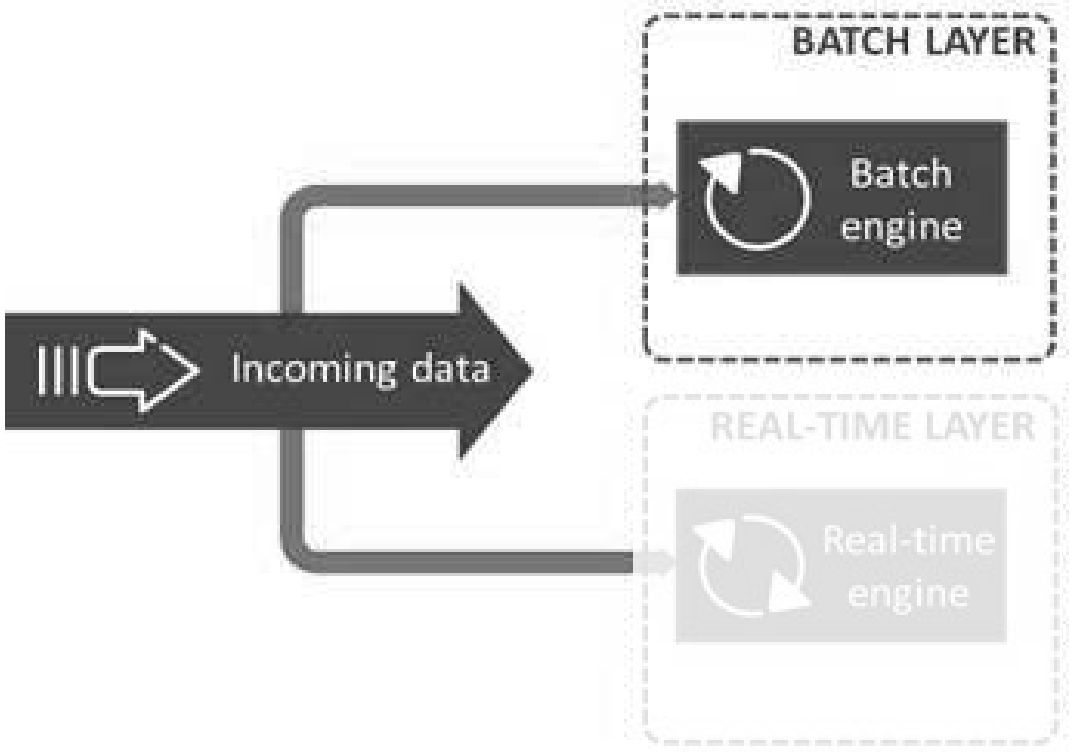




Lambda Architecture

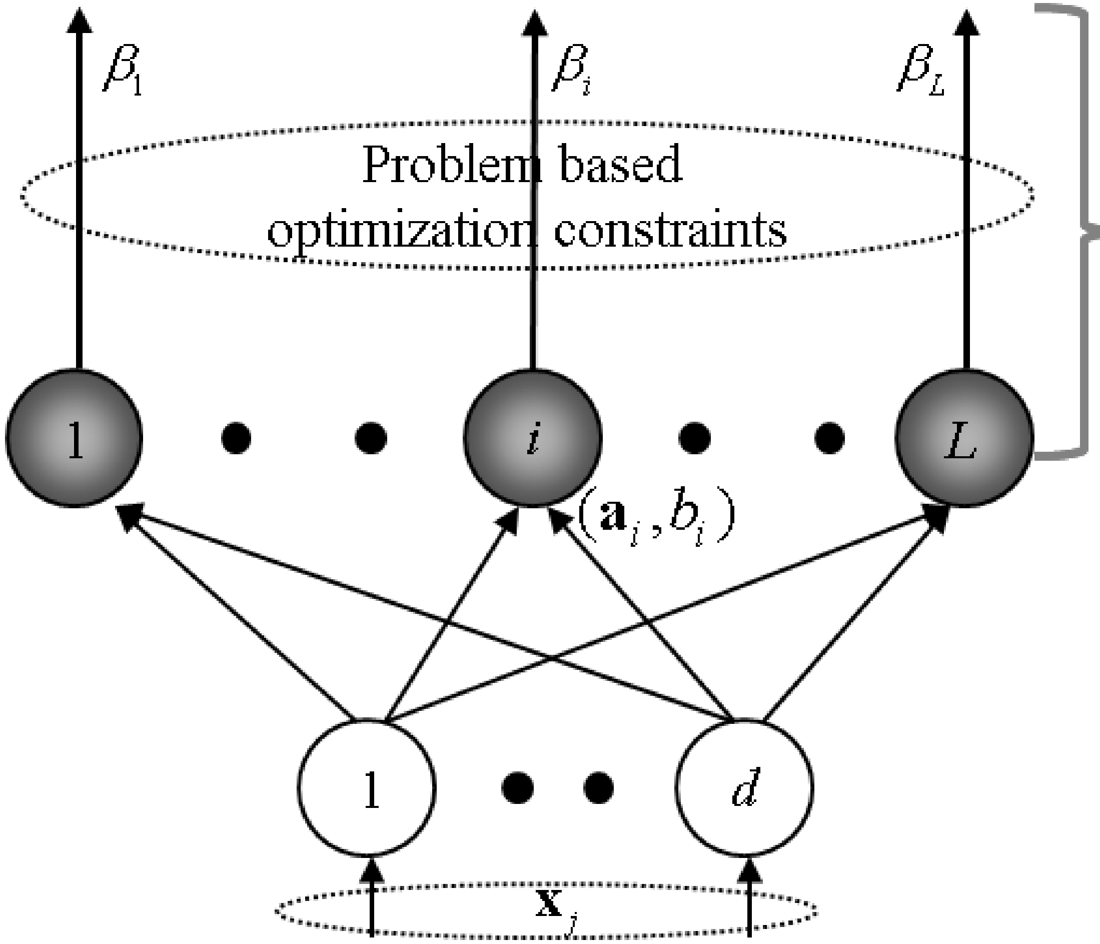


Lambda Architecture



Online Learning Multilayer Graph Regularized Extreme Learning Machine Auto-Encoder

ELM



Feature learning
Clustering
Regression
Classification

L Random Hidden Neurons (which need not be algebraic sum based) or other ELM feature mappings. Different type of output functions could be used in different neurons:

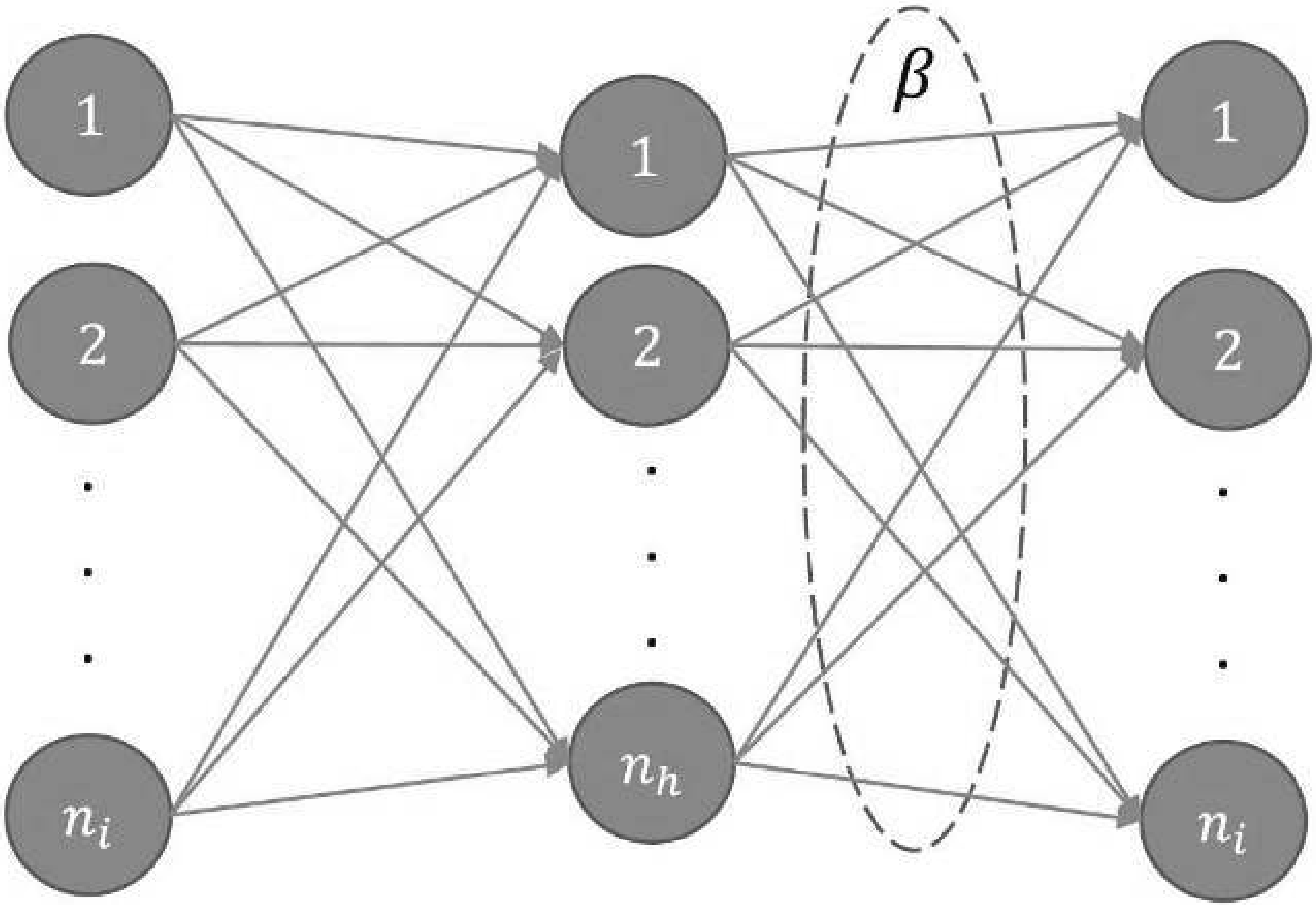
$$h_i(\mathbf{x}) = G_i(\mathbf{a}_i, b_i, \mathbf{x})$$

d Input Nodes

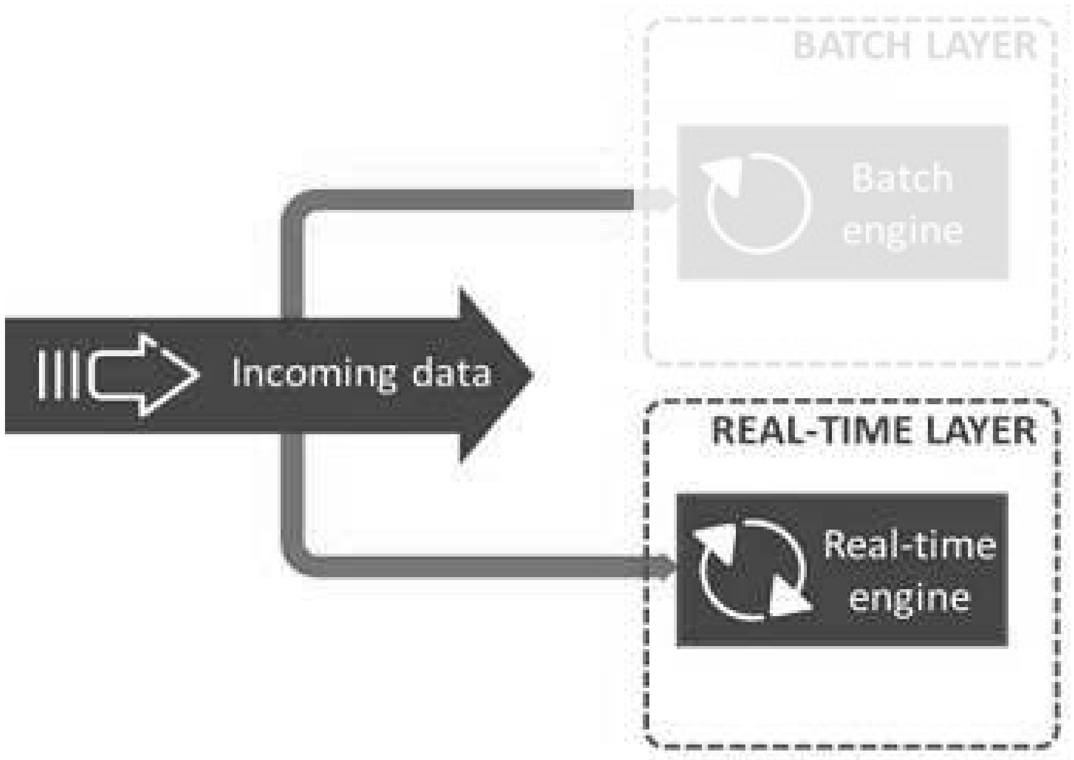
Online Sequential Learning ELM

- used over a sliding data window,
- can learn the sequential training observations online at arbitrary length (one by one or chunk by chunk) with fixed or varying length and discard the data for which the training has already been done,
- it has no prior knowledge about the amount of the observations which will be presented,
- do not require retraining whenever a new data is received,
- as soon as the learning procedure for the arrived observations is completed, the data is discarded.

ELM-AE



Lambda Architecture



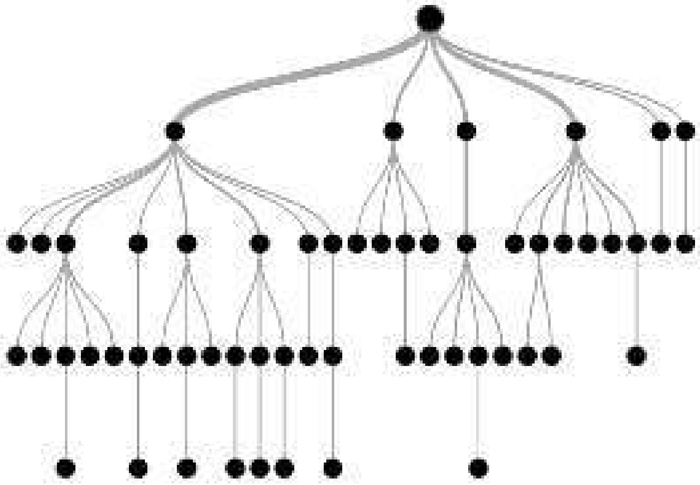
Adaptive Random Forests

Adaptive Random Forests

- The “Adaptive” part of ARF comes from its mechanisms to adapt to different kinds of concept drifts, given the same hyper-parameters.
- Specifically, the 3 most important aspects of the ARF algorithm are:
  - It adds diversity through resampling (“bagging”);
  - It adds diversity through randomly selecting subsets of features for node splits;
  - It has one drift and warning detector per base tree, which cause selective resets in response to drifts. It also allows training background trees, which start training if a warning is detected and replace the active tree if the warning escalates to a drift.
- There are no dependencies between trees.

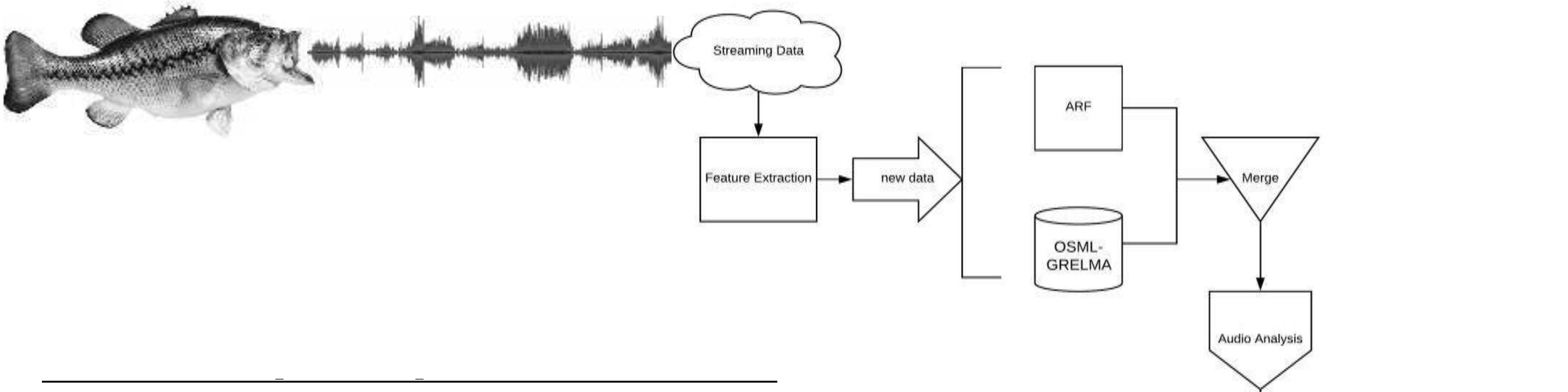
Algorithm 4. Adaptive Random Forests

function *ARF* $(m, n, \delta_w, \delta_d)$
  $T \leftarrow CreateTrees(n)$
  $W \leftarrow InitWeits(n)$
  $B \leftarrow \emptyset$
  while *HasNext(S) do*
    $(x, y) \leftarrow next(S)$
    for all $t \in T$ ***do***
      $\check{y} \leftarrow predict(t, x)$
      $W_{(t)} \leftarrow P\left(W_{(t)}, \check{y}, y\right)$
      RFTreeTrain (m, t, x, y)
      if $C\ (\delta_w, t, x, y)$ ***then***
        $b \leftarrow CreateTrees()$
        $B(t) \leftarrow b$
      end if
    end for
    for all $b \in B$ ***do***
      RFTreeTrain (m, b, x, y)
    end for
  end while
end function



Where:

1. m: maximum features evaluated per split;
2. n: total number of trees (n =|T |);
3. δw: warning threshold;
4. δd: drift threshold;
5. c(·): change detection method;
6. S: Data stream;
7. B: Set of background trees;
8. W(t):Tree t weight;
9. P(·): Learning performance estimation function.

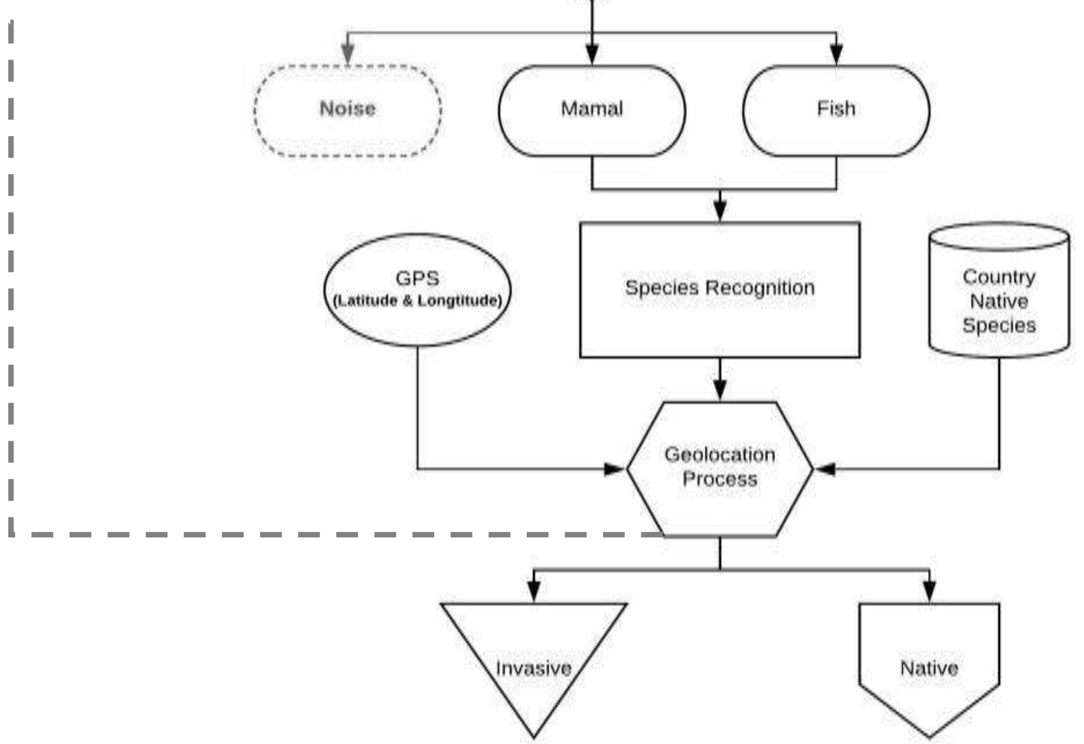


Algorithm 1: Geolocation Process

Input:
Recognized_Species;
Country;
Country_Native_Species;

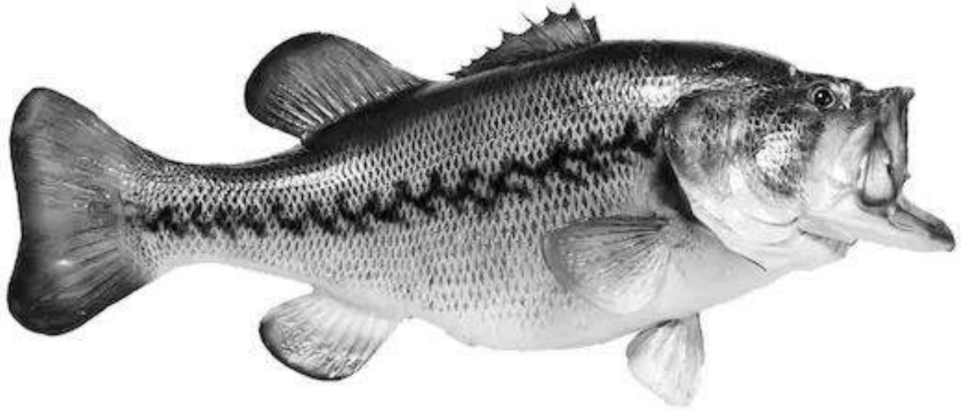
1: Read Recognized_Species, Country, Country_Native_Species;
2: **for** i=1 to Country_Native_Species [max] **do**
3: **if** Country_Native_Species [i]= Recognized_Species **then**
4: Recognized Species=Native_Species
5: **else**
9: Recognized Species=Invasive_Species
10: **end if**
11: **end**

Output:
Species Identity;



Feature Extraction

- **34 characteristics** related to statistical measurements obtained from the signal frequency information.
- Short-term feature sequences, using a frame size of **50 msec** and a **frame step of 25 msec** (50% overlap).
- Sampling rate of **44.1 kHz**
- **16-bit stereo resolution**
- Average duration **10.3 secs**



Datasets

- **Fishes:** **1076 sounds** belonging to **10 fish species** (e.g. *Bidyanus Bidyanus, Epinephelus Adscensionis, Cynoscion Regalis, etc*).
- **Mammals:** **836 sounds** belonging to **8 species of mammals** (e.g. *Delphinus Delphis, Erignathus Barbatus, Balaena Mysticetus, etc*).
- **Anthropogenic Sounds:** **684 sounds** belonging to **9 classes** (*Ship, Sonar, Zodiac, Wind Turbine, Scuba Noise, Bubble Curtain, etc*).
- **Natural Sounds:** **477 sounds** belong here classified in **6 clusters** (*Earthquake, Ice Cracking, Rainfall, Lightning, Waves, etc*).

Results

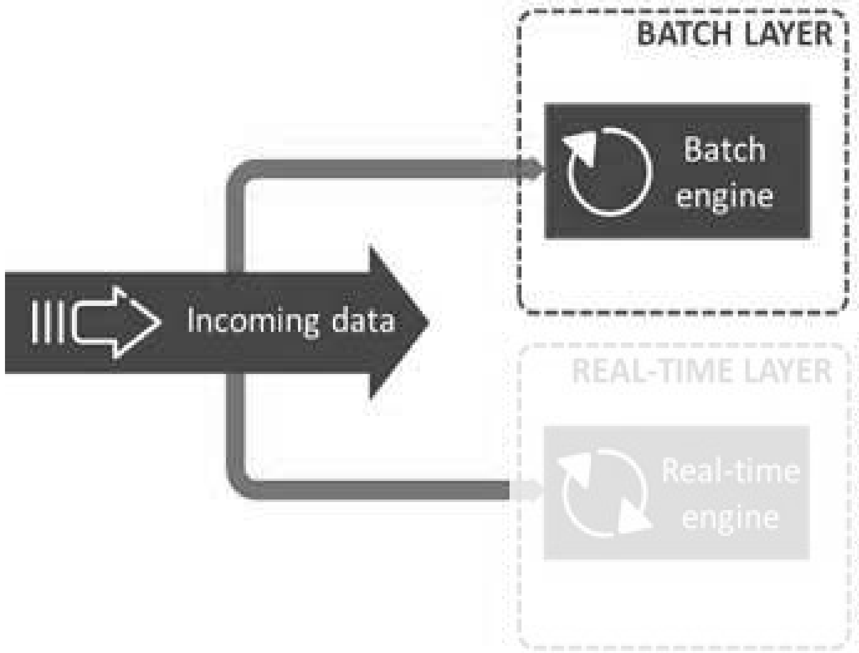


Table 1. Performance Metrics of Categories_Dataset

Classifier	Classification Accuracy & Performance Metrics					
	TA	RMSE	PRE	REC	F-Score	ROC Area
OSML-GRELMA	96.08%	0.1376	0.960	0.960	0.960	0.970

Table 2. Confusion Matrix of Categories_Dataset

Fishes	Mammals	Anthr_Sounds	Natural_Sounds	
1042	13	12	9	Fishes
14	**797**	17	8	Mammals
5	7	**659**	13	Anthr_Sounds
4	6	10	**457**	Natural_Sounds

Results

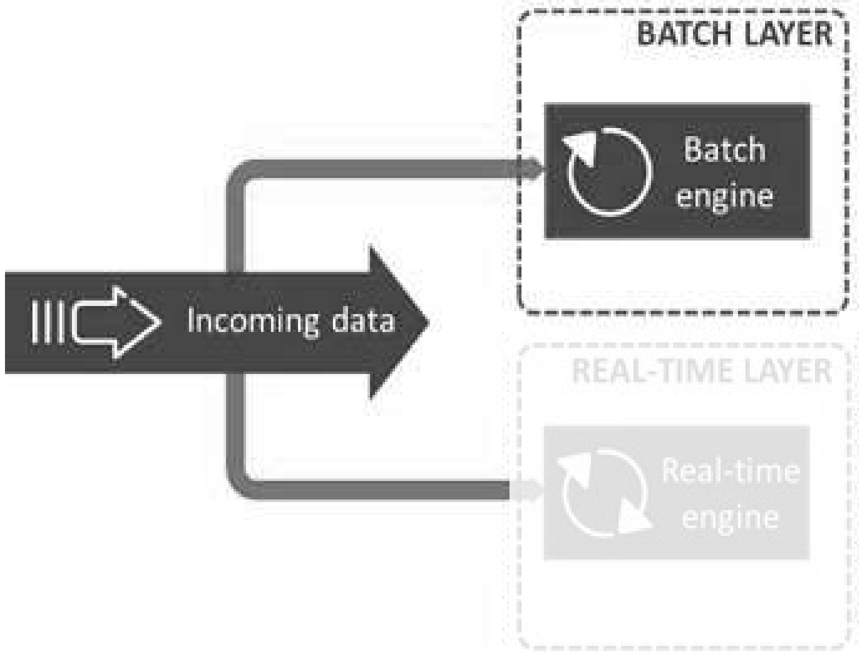


Table 3. Performance Metrics of Mammals_Dataset

Classifier	**Classification Accuracy & Performance Metrics**					
	TA	RMSE	PRE	REC	F-Score	ROC Area
OSML-GRELMA	92.18%	0.1571	0.922	0.922	0.922	0.955

Table 4. Confusion Matrix of Mammals_Dataset

a	b	c	d	e	f	g	h	
142	2	0	1	1	0	1	0	a = Delphinus Delphis
1	**101**	3	0	0	5	0	4	b = Erignathus Barbatus
1	2	**122**	1	0	0	0	2	c = Balaena Mysticetus
1	1	2	**61**	1	1	0	3	d = Phocoena Phocoena
2	2	3	1	**51**	0	2	2	e = Neophocaena Phocaenoides
2	0	2	0	1	**82**	0	2	f = Trichechus
2	0	0	0	0	1	**51**	1	g = Tursiops Truncates
2	2	1	1	1	0	1	**162**	h = Phoca Hispida

Results

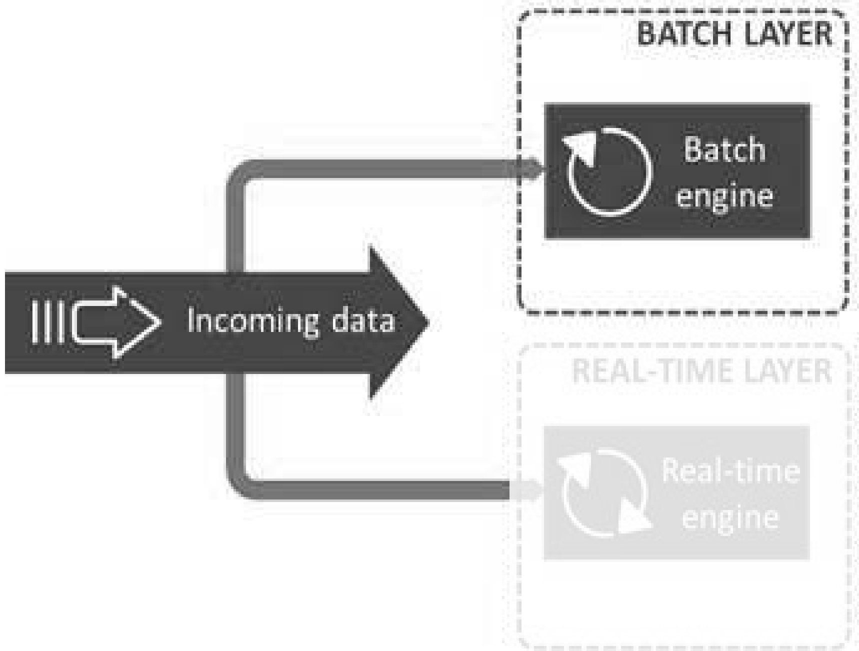


Table 5. Performance Metrics of Fishes_Dataset

Classifier	Classification Accuracy & Performance Metrics					
	TA	RMSE	PRE	REC	F-Score	ROC Area
OSML-GRELMA	87.91%	0.1512	0.879	0.879	0.879	0.920

Table 6. Confusion Matrix of Fishes_Dataset

a	b	c	d	e	f	g	h	i	j
139	5	1	2	1	0	1	0	1	3
4	**91**	4	1	3	0	0	2	4	0
0	3	**116**	1	2	0	2	4	2	2
1	0	1	**88**	1	0	0	1	0	1
0	3	1	1	**100**	0	0	2	1	2
1	0	0	0	1	**58**	0	2	0	3
1	0	1	0	0	0	**94**	2	0	0
3	5	6	1	3	1	1	**103**	1	8
0	3	2	0	3	0	0	1	**80**	3
1	0	3	1	3	1	1	3	1	**78**

a = Bid/nus Bidyanus, b = Epin/lus Adscen/nis, c = Cyn/cion Regalis, d = Cara/us Auratus
e = Cyp/nus Carpio, f = Rutilus Rutilus, g = SalmoTru, h = Oreo/mis Mossambicus
i = Micr/rus Salmoides, j = Oncor/hus Mykiss

Results

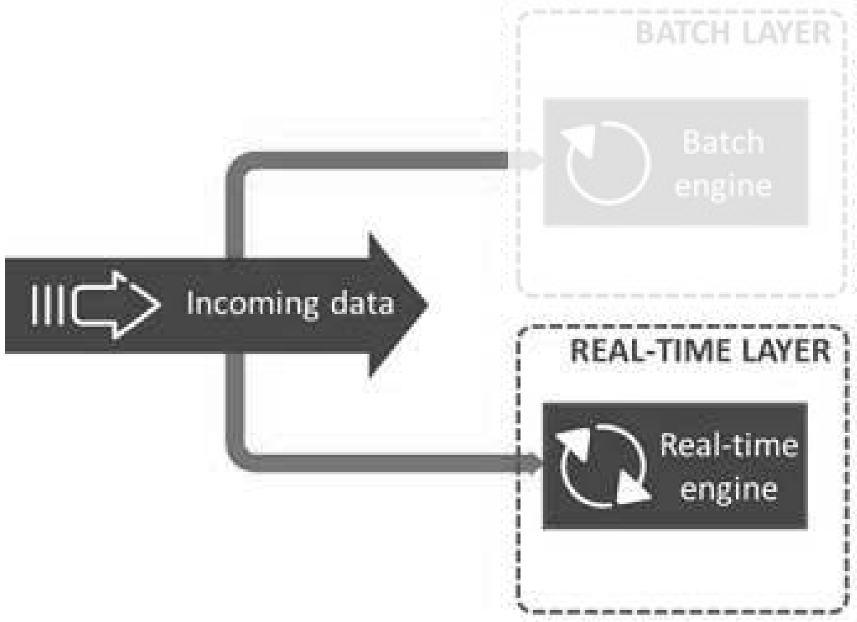


Table 7. Validation metrics when streaming data are used

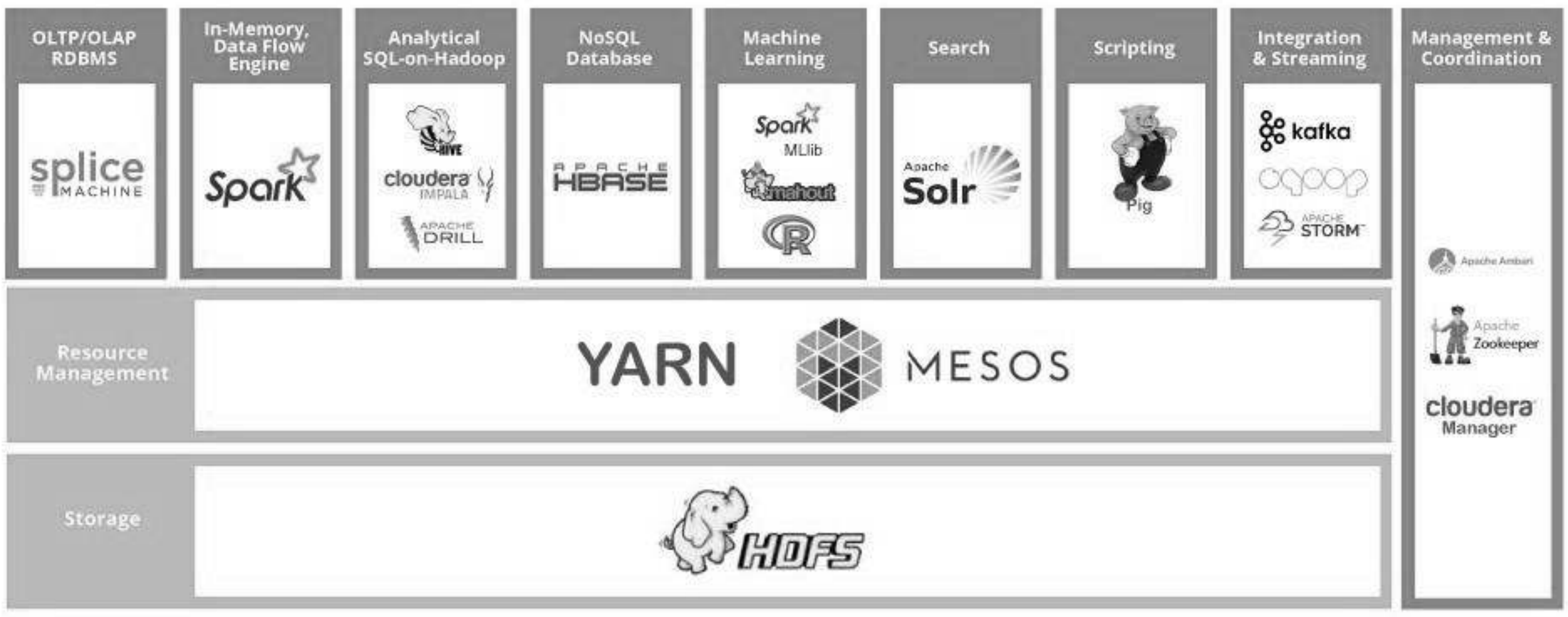
Classifier	Classification Accuracy & Performance Metrics		
	Accuracy	Kappa Statistic	Kappa Temporal Statistic
categories_dataset			
ARF	94.48%	73.91%	74.53%
mammals_dataset			
ARF	92.16%	71.37%	73.14%
fish_dataset			
ARF	88.11%	68.59%	70.36%

Innovations

- The implementation of an intelligent fully automated MH system.
- The Lambda architecture of the proposed system that combining the Online Learning Multilayer Graph Regularized Extreme Learning Machine Auto-Encoder and Adaptive Random Forests algorithms for the first time in the literature.
- The datasets used.

Future Work

- Further optimizing the parameters of the algorithm used.
- Lambda architecture in a parallel and distributed data analysis system (Hadoop).
- Self-improvement and meta-learning process of locating the species.



Any questions?

"That's all Folks!"