Artificial Intelligence in Engineering and Sciences

by Dr Varun Ojha University of Reading

at University of Surrey 06 December 2022



1. What are the AI Tools?

(scope)

2. What problems do they solve? (domain)

3. How do they solve problems? (algorithms)

What we want to know

1. to understand the data

(data collection, processing, and modelling)

2. to make some prediction

(forecasting)

3. to optimize some systems

(discovering appropriate parameters, variables, and settings)

Artificial Intelligence

to create intelligent machines that think (react) and act (work) like human beings

2018/00/16-17:32:38 - AICO 192: AICO D25

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Machine Learning

to create **machines** that learn from examples as living beings do

Learning

Video Source: <u>https://www.youtube.com/watch?v=Ak7bPuR2rDw</u> (Accessed on 21 February 2021)

Deep Learning

Source: https://becominghuman.ai/building-an-image-classifier-using-deep-learning-in-python-totally-from-a-beginners-perspective-be8dbaf22dd8







Optimization



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Optimization

to solve a **problem** that has a number of influencing factors that **need to attain certain value** in order to offer a **solution**

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Applications of Al

- 1. Engineering
- 2. Pharmacy & Drugs
- 3. Environment (Physiology & Architecture)
- 4. Civil Engineering
- 5. Physics
- 6. Biology
- 7. Hydrology
- 8. Climate Science

Electronics Engineering

Protection of health and life of sewer pipeline workers

Pattern Recognition

Intelligent recognizer for the component analysis of toxic mixture of (sewer) gases



Gas mixture collection

Sensor array formation

Data collection and simulation

Pattern Recognition

Prototype of Intelligence Sensor



This was the objective



We managed to get this one nonetheless! (2011-2013)

Pharmaceutical

Drug manufacturing process variables and drug property analysis

Pharmaceutical (Drugs Production)





Pharmaceutical







Tablet Properties (Compressibility)



Granule Size Distribution + (die filling process) (Density, Hardness,

Porosity) + (Milling speed etc.)



Powder Properties

(Flowability, compactibility) + (Roller gap and roller speed)

Properties

Particle

(Material type, density, size, shape and etc.)

Ojha et al. (2017) Neural Computing and Applications: https://arxiv.org/abs/1709.04318

Variable Identification of Pharmaceutical Industrial Processes

Prediction of the mass of deposited drug powder



Photron	FASTCAM SA4 mode		
1000 fps	1/1000 sec	512 x 512	
End	frame : -1150	-1150 ms	
Date : 2015/1/14	Time : 19:41		



Ojha et al. (2017) Neural Computing and Applications

Drug Dissolution

Ojha VK et al. (2015) International Journal of Nanomedicine



Three Hundred Descriptors of Drug Properties

PLGA: poly(lactic-co-glycolic acid)

SI No	Group name	No of features	Importance
L	Protein descriptors	85	Describes the type of molecules and proteins used
2	Formulation characteristics	17	Describe the molecular properties such as molecular weight, particle size, etc
3	Plasticizer	98	Describe the properties such as fluidity of the material used
4	Emulsifier	99	Describe the properties of stabilizing/increase the pharmaceutical product life
5	Time in days	L	Time taken to dissolve
6	% of molecules dissolved	L	Output

Abbreviations: PLGA, poly(lactic-co-glycolic acid); SI, serial; No, number.

Ojha et al. (2015) International Journal of Nanomedicine https://doi.org/10.2147/IJN.S71847

Balancing Prediction and Feature Selection

Algorithm	RMSE E_t	No. of features
MLP	14.3	17
Neural Tree	13.2	15
REP Tree	13.3	15
GPR	14.9	15
MLP	15.2	15
MLP	15.4	11
Type 1 Tree	18.6	7
Type 2 Tree	15.2	4

Ojha et al. (2018) *IEEE Transactions on Fuzzy Systems https://arxiv.org/abs/1705.05769*

A Tree Model for Future Use

Can we also explain how the prediction was made?



If protein is A and plasticizer is B, Then % molecule dissolution is X

Ojha et al. (2018) *IEEE Transactions on Fuzzy Systems https://arxiv.org/abs/1705.05769*

Build Environment

Understanding impact of environment and urban dynamics on humans

Perception of the Environment



Ojha et al. (2019) Information Sciences | Buš & Ojha (2017), ETH Zurich

Perceptual Experience

















Ojha et al. (2019) *Information Sciences* | Buš & Ojha (2017), *ETH Zurich* https://arxiv.org/abs/1812.06128

Civil Engineering

Structure buckling analysis

Civil Engineering Problem



Civil Engineering Problem



A tiny version of Millennium Dome can be the following structure





Hrinda, G. (2010, April). Snap-through instability patterns in truss structures. In 51st AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference 18th AIAA/ASME/AHS Adaptive Structures Conference 12th (p. 2611).

Civil Engineering Problem



Fig A. Adaptive Hypersphere Search Algorithm for

Structural Static Analysis

Ojha et al (2022), Engineering Application of Artificial Intelligence https://arxiv.org/pdf/2211.07519.pdf



Fig B. Equilibrium Path traced using Adaptive Hypersphere Search Algorithm



Deformed shape D

Ojha et al (2022), Engineering Application of Artificial Intelligence

Physics

Solar cell design and characterization

Solar Cell – Energy Optimization





Ojha et al. (2021) Energy Systems https://arxiv.org/abs/2109.07279

Solar Cell

Cost and Efficiency Trade-offs for its Usage





Smooth back reflector Al, Not Doped ZnO —
Rough back reflector Ag, Not Doped ZnO ———
Smooth back reflector Ag, Not Doped ZnO —*-
Smooth back reflector Al, Lowly Doped ZnO —
Smooth back reflector Ag, Lowly Doped ZnO —
Rough back reflector Ag, Lowly Doped ZnO ——
Smooth back reflector AI, SnO2
nooth back reflector Al, Normally Doped ZnO
ooth back reflector Ag, Normally Doped ZnO —
ough back reflector Ag, Normally Doped ZnO ———
Smooth back reflector Ag, SnO2
Rough back reflector Ag, SnO2
nooth back reflector Al, Optimally Doped ZnO
ooth back reflector Ag, Optimally Doped ZnO ———
ough back reflector Ag, Optimally Doped ZnO —

Biology

Metabolic engineering (searching for best strains)

Role of Yeasts in Food Production







Metabolic Engineering for Chemical Production



Optimal Strains of Yeast



Hydrology

Prediction of flood events

Hydrology: Flood Event Prediction

A collaboration with Meteorology (Prof. Sarah Dance and Remy Vandaele)



Fig. Time-series sequence of images of river. Blue pixels are water segmentation by using deep learning models



Credit: Farson Digital Watercams https://www.farsondigitalwatercams.com/locations/keswick_greta

Vandaele, Dance, and Ojha, (2020), *GCPR* https://doi.org/10.1007/978-3-030-71278-5

Hydrology: Flood Event Prediction

A collaboration with Meteorology (Prof. Sarah Dance and Remy Vandaele)



STRENSHAM LOCK





TEWKESBURY MARINA



Fig A. Customized dataset:

Landmark annotation of waterline

Vandaele, Dance, and Ojha, (2021) Hydrology and Earth System Sciences

https://doi.org/10.5194/hess-25-4435-2021



EVESHAM



STRENSHAM LOCK



TEWKESBURY MARINA



Fig B. Best window identification for prediction accuracy.We achieve 94% accuracy in correctly predicting real flood events.

Climate Science

Non-intrusive modelling of dynamical systems

Predicting Instabilities in Chaotic Systems



Machine Learning Algorithms to Use

Supervised recurrent neural networks for the reconstruction short term dynamics



Ayers, Lau, Amezcua, Carrassi, Ojha (in rev. 2022) Quarterly Journal of the Royal Meteorological Society

What LOSS function can we use?

We can consider two types of losses:

• Purely Data Driven loss (Neural Nets):

• loss =
$$\frac{1}{N} \sum (x_{t+1} - f(x_t))^2$$

• Physics Informed loss (Physics Informed Neural Nets)

• loss =
$$\frac{1}{N} \sum (x_{t+1} - f(x_t))^2$$
 + physics (e.g., $|RK_4(x_t) - RK_4(f(x_t)|)$

Data Driven Neural Nets

(prediction of short term dynamics)



Physics Informed Neural Nets

(prediction of short term dynamics)

Symmetric Convolutional Autoencoder

Plastic Waste Pollution (Input Video)

AI Solution

(Output Video)

Jaikumar P et al. (2020) ISDA, https://centaur.reading.ac.uk/98569/

v.k.ojha@reading.ac.uk