Deep Dive into Deep Learning

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DEPARTMENT OF ELECTRICAL ENGINEERING

ORS Research Design & Data Analysis Lab

Office of Research and Scholarship

ANALYSIS PLATFORM

MATLAB R2021b

https://www.mathworks.com/academia/tah-portal/university-of-texas-at-tyler-1108545.html

ANALYSIS PLATFORM

OUTLINE

➢ INTRODUCTION

➢ CHALLENGES OF BIOMEDICAL DATA ANALYSIS

➢ DIFFERENT DEEP LEARNING APPROACHES WITH EXAMPLES

➢ QUESTIONS

OUTLINE

➢INTRODUCTION

➢CHALLENGES OF BIOMEDICAL DATA ANALYSIS

➢DIFFERENT DEEP LEARNING APPROACHES WITH EXAMPLES

➢QUESTIONS

INTRODUCTION

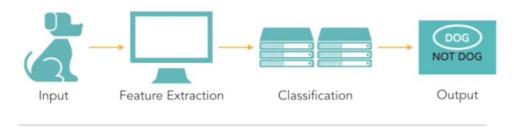➢ What is Machine Learning ?

▪ Machine Learning is a field of study that gives computers the ability to "learn" without being explicitly programmed

- Prediction

- Classification

Samuel AL, IBM J. Research & Development, 1959, vol. 3 (3), 210-229

INTRODUCTION

➢ What is **Deep** Learning?

▪ Deep learning is a branch of machine learning that teaches computers to do what comes naturally to humans: learn from experience.

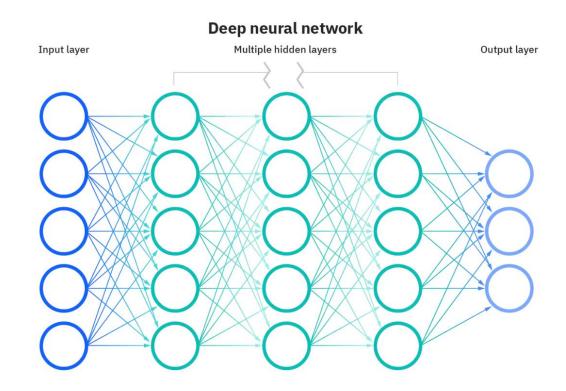▪ Deep learning uses deep neural network with several layers to learn.

TRANDITIONAL MACHINE LEARNING

Input → Feature Extraction → Classification → Output (DOG NOT DOG)

DEEP LEARNING

Input → Feature Extraction + Classification → Output (DOG NOT DOG)

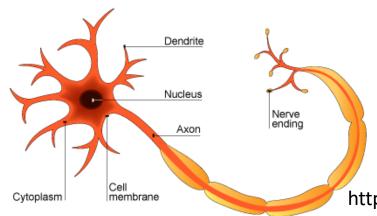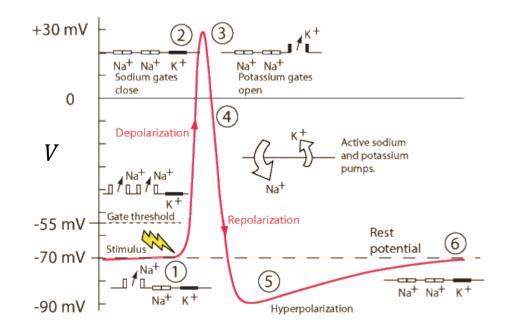https://www.guru99.com/machine-learning-vs-deep-learning.html

INTRODUCTION

➤ What is **Deep** Learning?

■ Deep learning describes models that utilize multiple layers to represent latent features at a higher and more abstract level

■ The representations are learned from data rather than constructed by human engineers

Deep neural network

Input layer   Multiple hidden layers   Output layer

https://www.ibm.com/cloud/learn/neural-networks

INTRODUCTION

➢ Inspiration from biological Neuron

▪ All or none

▪ Frequency rather amplitude helps in information processing
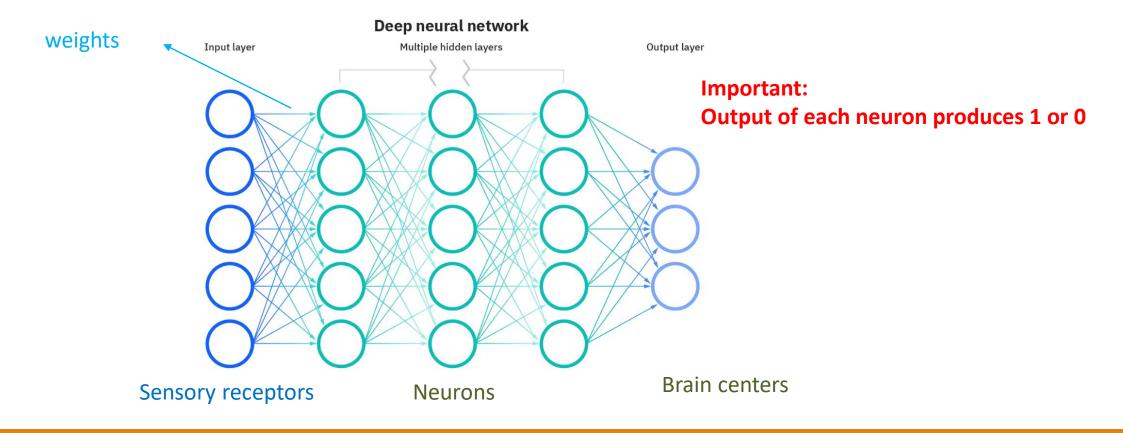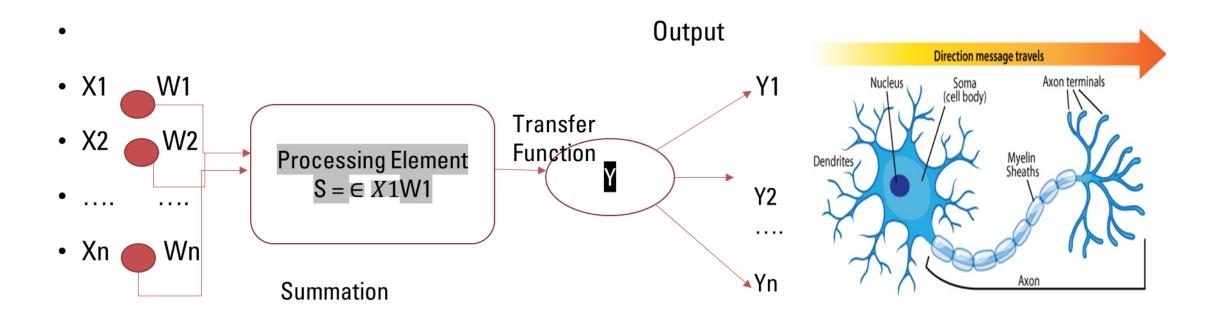

Biological Neuron

http://hyperphysics.phy-astr.gsu.edu/hbase/Biology/imgbio/actpot4.gif
https://pmgbiology.files.wordpress.com/2015/02/5d3d66ef622165ae607b3c02f6e603c524e ececf.gif

INTRODUCTION

➢From biological neural to artificial neural network

Deep neural network
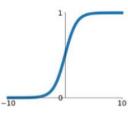
weights

Input layer

Multiple hidden layers

Output layer

Important:
Output of each neuron produces 1 or 0

Sensory receptors   Neurons   Brain centers

INTRODUCTION

➤ **How Artificial Neural Network Works?**

INTRODUCTION

➤ Activation Functions

Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$

tanh

$\tanh(x)$

ReLU

$\max(0, x)$

Leaky ReLU
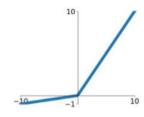
$\max(0.1x, x)$
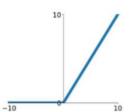
Maxout

$\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

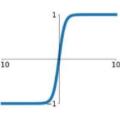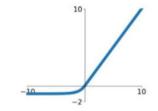$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$
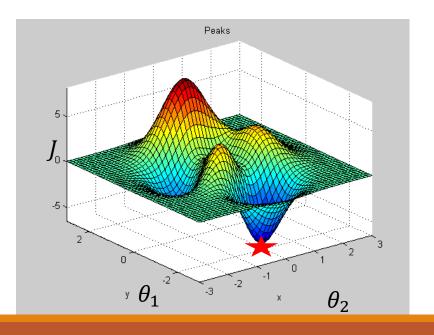
APPROACHES

➢Gradient Descent

$$\hat{y}^i = \theta_0 + \theta_1 x_1^i + \theta_2 x_2^i + \cdots \ldots \ldots + \theta_n x_n^i \qquad i = 1, 2, \ldots \ldots m$$
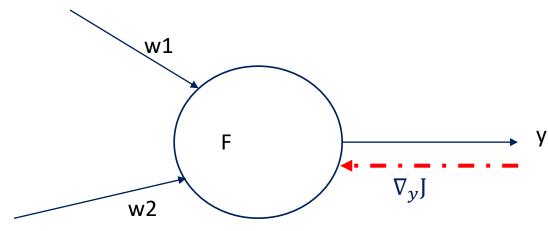
$$J = \left\langle (\hat{y}^i - y^i)^2 \right\rangle = (\hat{Y} - Y)^T (\hat{Y} - Y) = \frac{1}{m} \sum_{i=1}^{m} (\theta^T X^i - y^i)^2$$

$$\theta^{k+1} = \theta^k - \gamma \nabla_\theta J(\theta) \quad \text{(Standard Machine Learning)}$$
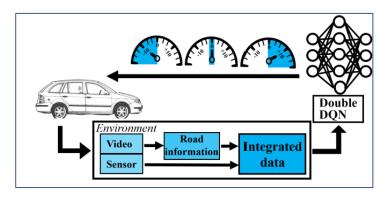
Back Propagation Algorithm (ANN)

$$w^{k+1} = w^k - \gamma \nabla_w J$$

$$\nabla_w J = \nabla_y J \nabla_w y$$

INTRODUCTION

➤ Application of Deep Learning

Cruise Assistance
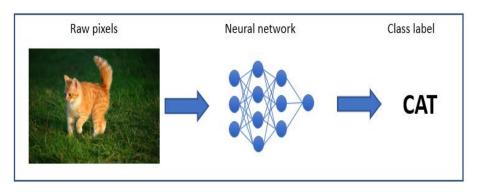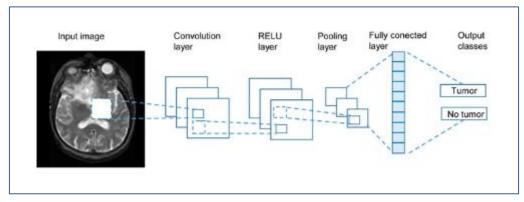
Image Recognition

Medical Imaging

OUTLINE

➢INTRODUCTION

➢CHALLENGES OF BIOMEDICAL DATA ANALYSIS

➢DIFFERENT DEEP LEARNING APPROACHES WITH EXAMPLES

➢QUESTIONS

BIOMEDICAL (BIG) DATA

➢NEED A SPECIFIC RESEARCH QUESTION (HYPOTHESIS)

➢FROM BIG DATA TO CLINICAL IMPACT IS STILL UNCLEAR

Scientific hypothesis, an idea that proposes a tentative explanation about a phenomenon or a narrow set of phenomena observed in the natural world. The two primary features of a scientific hypothesis are falsifiability and testability

Source: https://www.britannica.com/science/scientific-hypothesis

BIOMEDICAL (BIG) DATA

➢PHYSIOLOGICAL / BEHAVIORAL / DEMOGRAPHICS

- Traditional Data Collection (Controlled Conditions)

- Electronic Health Records (Notes, Vital Signs, Demographics, Lab Results..)

- Sensor Data

- Social Media Data

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BIOMEDICAL (BIG) DATA

- Traditional Data Collection (Controlled Conditions)

Very expensive

Randomized Control Trials (Inclusion/ Exclusion Criteria)

Population sample must match the actual population (selection bias)

Sanson-Fisher, R.W., Bonevski, B., Green, L.W. and D'Este, C., 2007. Limitations of the randomized controlled trial in evaluating population-based health interventions. *American journal of preventive medicine*, *33*(2), pp.155-161.

BIOMEDICAL (BIG) DATA

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Zadrozny, B., 2004, July. Learning and evaluating classifiers under sample selection bias. In *Proceedings of the twenty-first international conference on Machine learning* (p. 114).

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BIOMEDICAL (BIG) DATA

- Electronic Health Records

  Demographics, current and past diagnosis, lab results, prescription drugs, notes, radiological images, ……

  Subjective vs Objective

BIOMEDICAL (BIG) DATA

- Electronic Health Records

Medical Concept Extraction

Patient Trajectory Modeling

Disease Inference

Clinical Decision Support System

BIOMEDICAL (BIG) DATA

- Electronic Health Records (Notes, Vital Signs, Demographics, ….)

Missing Data

Sample Size

Miss classification error

Gianfrancesco, M.A., Tamang, S., Yazdany, J. and Schmajuk, G., 2018. Potential biases in machine learning algorithms using electronic health record data. *JAMA internal medicine*, *178*(11), pp.1544-1547.

BIOMEDICAL (BIG) DATA

- Electronic Health Records (Notes, Vital Signs, Demographics, ….)

From traditional machine learning to deep learning:

Features are derived directly from data

Based on Artificial Neural Networks

Shickel, B., Tighe, P.J., Bihorac, A. and Rashidi, P., 2017. Deep EHR: a survey of recent advances in deep learning techniques for electronic health record (EHR) analysis. *IEEE journal of biomedical and health informatics*, *22*(5), pp.1589-1604.

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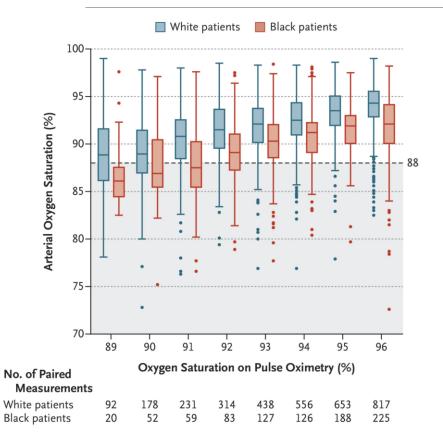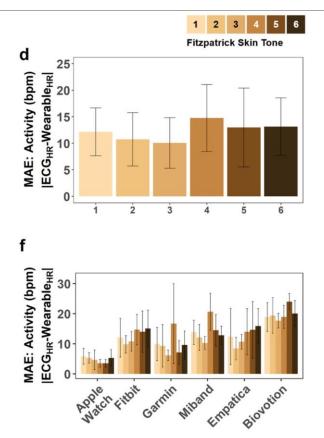
- Sensor Data

Sensor Design   : Differential characteristics

Data are nonstationary   : Feature extraction methods are stationary

Data has multiscale structure : Analytical tools fails to capture such scales

Noise & Artifacts   : Noise/ artifacts may have useful information

BIOMEDICAL (BIG) DATA

- Sensor Data

Sensor Design	: Differential characteristics
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BIOMEDICAL (BIG) DATA

Sjoding, M.W., Dickson, R.P., Iwashyna, T.J., Gay, S.E. and Valley, T.S., 2020. Racial bias in pulse oximetry measurement. *New England Journal of Medicine*, *383*(25), pp.2477-2478.

Bent, B., Goldstein, B.A., Kibbe, W.A. and Dunn, J.P., 2020. Investigating sources of inaccuracy in wearable optical heart rate sensors. *NPJ digital medicine*, *3*(1), pp.1-9.
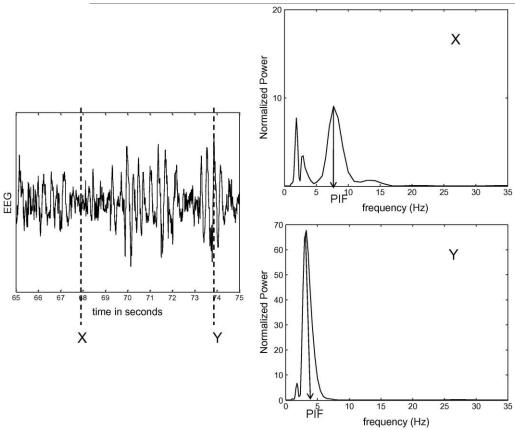
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BIOMEDICAL (BIG) DATA

Indic, P. and Narayanan, J., 2011. Wavelet based algorithm for the estimation of frequency flow from electroencephalogram data during epileptic seizure. *Clinical neurophysiology*, *122*(4), pp.680-686.
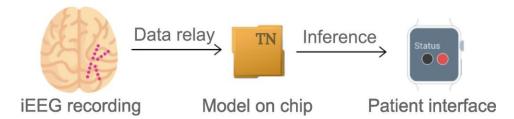
Kiral-Kornek, I., Roy, S., Nurse, E., Mashford, B., Karoly, P., Carroll, T., Payne, D., Saha, S., Baldassano, S., O'Brien, T. and Grayden, D., 2018. Epileptic seizure prediction using big data and deep learning: toward a mobile system. *EBioMedicine*, *27*, pp.103-111.
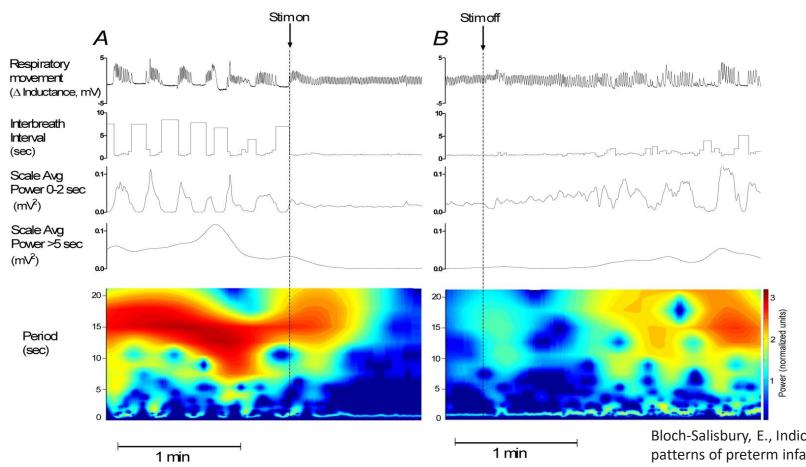
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BIOMEDICAL (BIG) DATA

Bloch-Salisbury, E., Indic, P., Bednarek, F. and Paydarfar, D., 2009. Stabilizing immature breathing patterns of preterm infants using stochastic mechanosensory stimulation. *Journal of Applied Physiology*, *107*(4), pp.1017-1027.
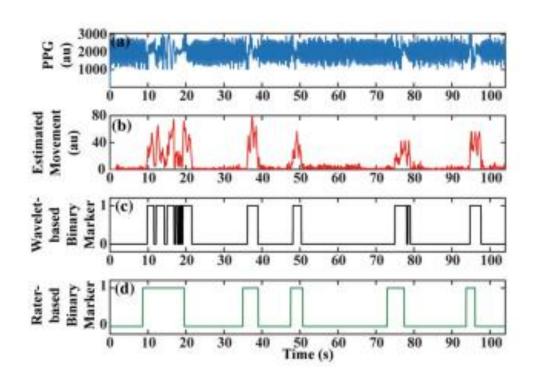
BIOMEDICAL (BIG) DATA

- Sensor Data

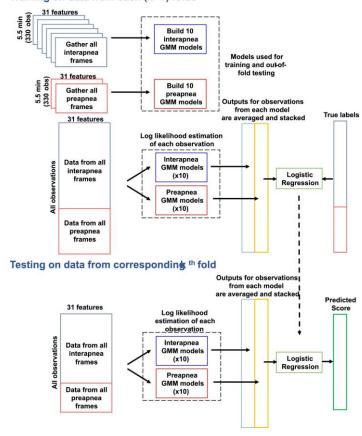|	
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BIOMEDICAL (BIG) DATA

Zuzarte, I., Sternad, D. and Paydarfar, D., 2021. Predicting apneic events in preterm infants using cardio-respiratory and movement features. *Computer Methods and Programs in Biomedicine*, *209*, p.106321.

BIOMEDICAL (BIG) DATA

Bias:

Historical bias	: Structural issue with data collection
Representation bias	: Effect of sampling
Measurement bias	: Measurement of a specific feature
Evaluation bias	: Model iteration and evaluation
Aggregation bias	: Flawed assumptions

Suresh, H. and Guttag, J.V., 2019. A framework for understanding unintended consequences of machine learning. *arXiv preprint arXiv:1901.10002, 2*.

BIOMEDICAL (BIG) DATA

Challenges:

Conceptual : Standards, Physician's intuition, Reasoning

Technical : Limitations in sensors & algorithms

Humanistic : Values & duties, ethics

Interpretability : From black box to clinical inference

Quinn, T.P., Senadeera, M., Jacobs, S., Coghlan, S. and Le, V., 2021. Trust and medical AI: the challenges we face and the expertise needed to overcome them. *Journal of the American Medical Informatics Association*, *28*(4), pp.890-894.

OUTLINE

➢INTRODUCTION

➢CHALLENGES OF BIOMEDICAL DATA ANALYSIS

➢DIFFERENT DEEP LEARNING APPROACHES WITH EXAMPLES
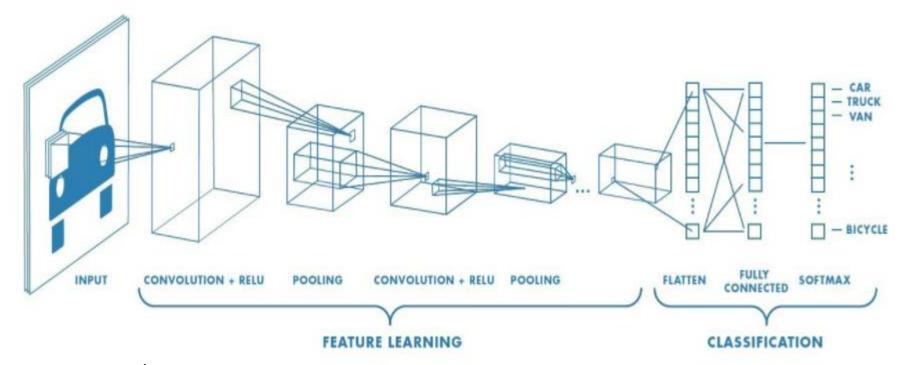
➢QUESTIONS

OUTLINE

➢DIFFERENT DEEP LEARNING APPROACHES WITH EXAMPLES

Convolutional Neural Network
Long Short-Term Memory

OUTLINE

➢DIFFERENT DEEP LEARNING APPROACHES WITH EXAMPLES

Convolutional Neural Network
Long Short-Term Memory

APPROACHES

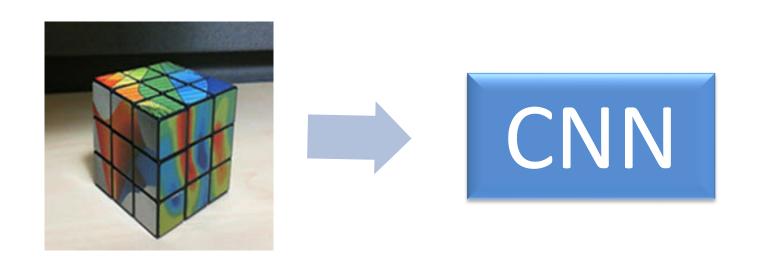➢Convolutional Neural Network (Finite Impulse Response)

APPROACHES

➤ Convolutional Neural Network (Pretrained Network)

GoogLeNet, a pretrained deep convolutional neural network (CNN or ConvNet)

APPROACHES

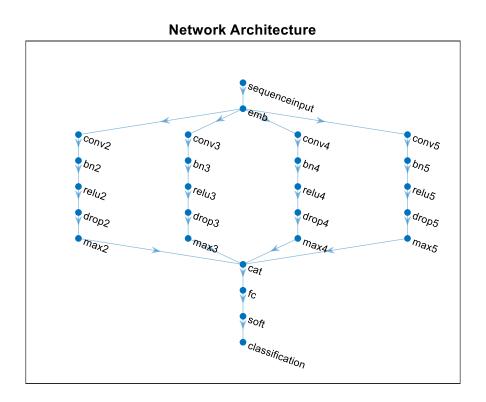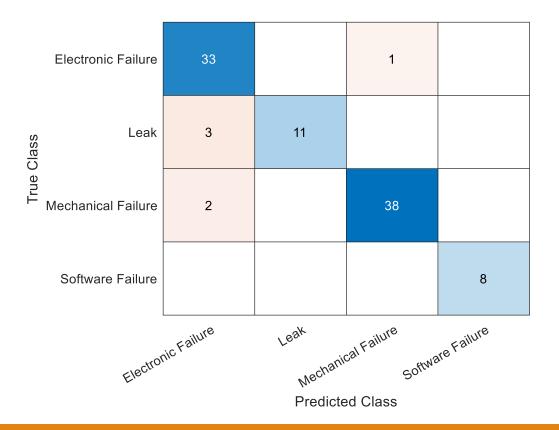➢ Example 1: Simple Image Classification using GoogleNET (using App)

MathWorks Cube

APPROACHES

➤ Example 2: Classify Text Data Using Convolutional Neural Network
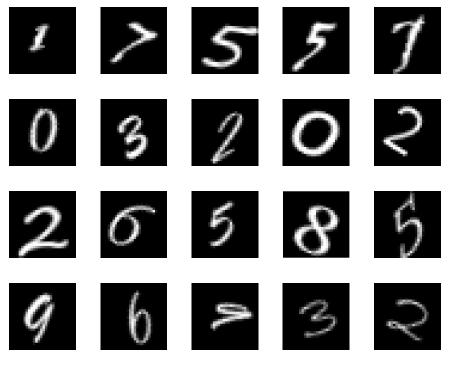
| Description	Category	Urgency	Resolution	Cost
{'Items are occasionally getting stuck in the scanner spools.' }	{'Mechanical Failure'}	{'Medium'}	{'Readjust Machine' }	45
{'Loud rattling and banging sounds are coming from assembler pistons.'}	{'Mechanical Failure'}	{'Medium'}	{'Readjust Machine' }	35
{'There are cuts to the power when starting the plant.' }	{'Electronic Failure'}	{'High' }	{'Full Replacement' }	16200
{'Fried capacitors in the assembler.' }	{'Electronic Failure'}	{'High' }	{'Replace Components'}	352
{'Mixer tripped the fuses.' }	{'Electronic Failure'}	{'Low' }	{'Add to Watch List' }	55
{'Burst pipe in the constructing agent is spraying coolant.' }	{'Leak' }	{'High' }	{'Replace Components'}	371
{'A fuse is blown in the mixer.' }	{'Electronic Failure'}	{'Low' }	{'Replace Components'}	441
{'Things continue to tumble off of the belt.' }	{'Mechanical Failure'}	{'Low' }	{'Readjust Machine' }	38
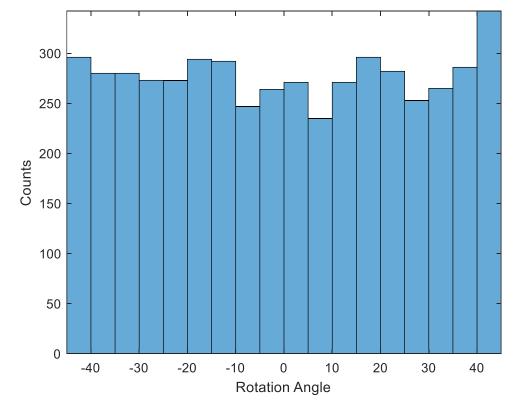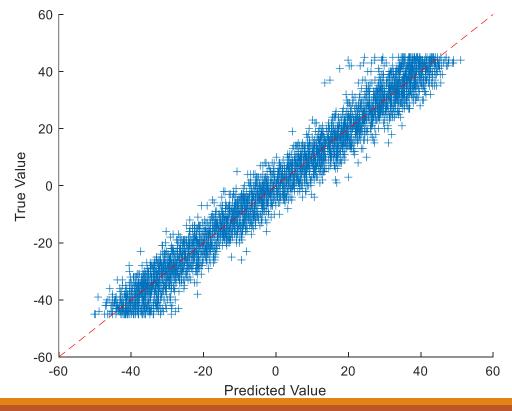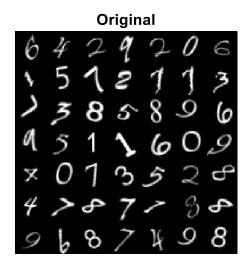
APPROACHES

➢ Example 2: Classify Text Data Using Convolutional Neural Network

Network Architecture

APPROACHES

➢Example 2: Classify Text Data Using Convolutional Neural Network

APPROACHES

➢Example 3: Regression model using CNN to predict the angles of rotation of handwritten digits.

APPROACHES

➤ Example 3: Regression model using CNN to predict the angles of rotation of handwritten digits.

APPROACHES

➢Example 3: Regression model using CNN to predict the angles of rotation of handwritten digits.

APPROACHES

➢ Example 3: Regression model using CNN to predict the angles of rotation of handwritten digits.

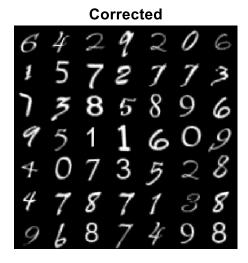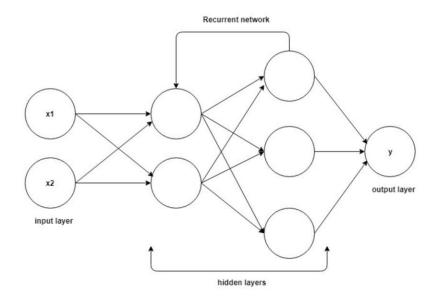Original   Corrected

OUTLINE

➢DIFFERENT DEEP LEARNING APPROACHES WITH EXAMPLES

Convolutional Neural Network
Long Short-Term Memory

APPROACHES

➢ Long Short-Term Memory (LSTM) Network (Infinite Impulse Response)
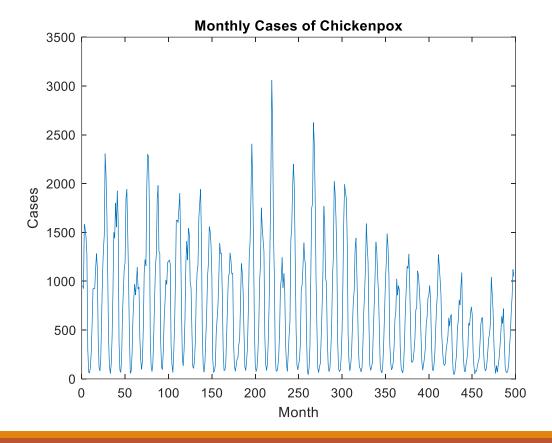
Special category of network that are suitable for learning long-term dependencies.

https://towardsdatascience.com/machine-learning-recurrent-neural-networks-and-long-short-term-memory-lstm-python-keras-example-86001ceaaebc
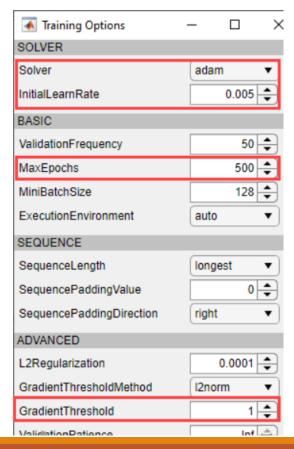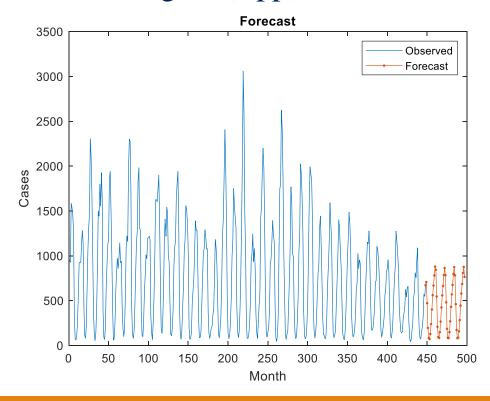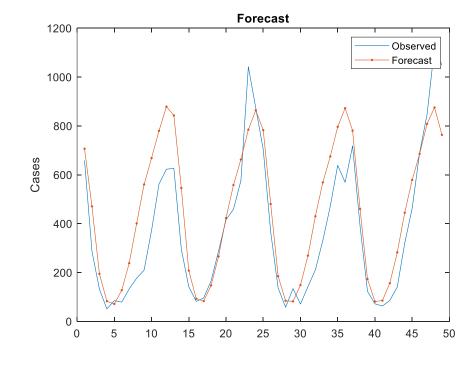
APPROACHES

Example 4: LSTM Regression Network for Time Series Forecasting Using Deep
Network Designer (App)

APPROACHES

Example 4: LSTM Regression Network for Time Series Forecasting Using Deep Network Designer (App)

APPROACHES

Example 4: LSTM Regression Network for Time Series Forecasting Using Deep
Network Designer (App)

CONCLUSION

➢Deep Learning Networks can be used for regression and classification

➢Forecasting or Prediction is a salient feature of ANN

➢Need large amount of data to train the models

➢Special Attention to be given to the challenges in dealing with biomedical data

THANK YOU

Center for Health Informatics & Analytics — UT Tyler

SBIR: RAE (Realize, Analyze, Engage) - A digital biomarker based detection and intervention system for stress and carvings during recovery from substance abuse disorders.
PIs: M. Reinhardt, S. Carreiro, P. Indic

STARs Award

The University of Texas System
P. Indic (PI, UT Tyler)

Research Design & Data Analysis Lab
Office of Research, Scholarship, and Sponsored Programs

Design of a wearable sensor system and associated algorithm to track suicidal ideation from movement variability and develop a novel objective marker of suicidal ideation and behavior risk in veterans.
Clinical Science Research and Development Grant (approved for funding),
P. Indic (site PI, UT-Tyler)
E.G. Smith (Project PI, VA)
P. Salvatore (Investigator, Harvard University)

Pre-Vent

National Institute Of Health Grant
P. Indic (Analytical Core PI, UT-Tyler)
N. Ambal (PI, Univ. of Alabama, Birmingham)

ViSiON

National Institute Of Health Grant
P. Indic (Co-Investigator & site PI , UT-Tyler)
P. Ramanand (Co-Investigator, UT-Tyler)
N. Ambal (PI, Univ. of Alabama, Birmingham)

QUESTIONS