APPLICATION OF MACHINE LEARNING AND DEEP LEARNING FOR SRF CAVITY FAULT DETECTION AND CLASSIFICATION

KHAN IFTEKHARUDDIN AND

LASITHA VIDYARATNE

VISION LAB

DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

OLD DOMINION UNIVERSITY

NORFOLK, VA

*This work is performed in collaboration with Chris Tennant and Ana Solopova, JLAB

OUTLINE

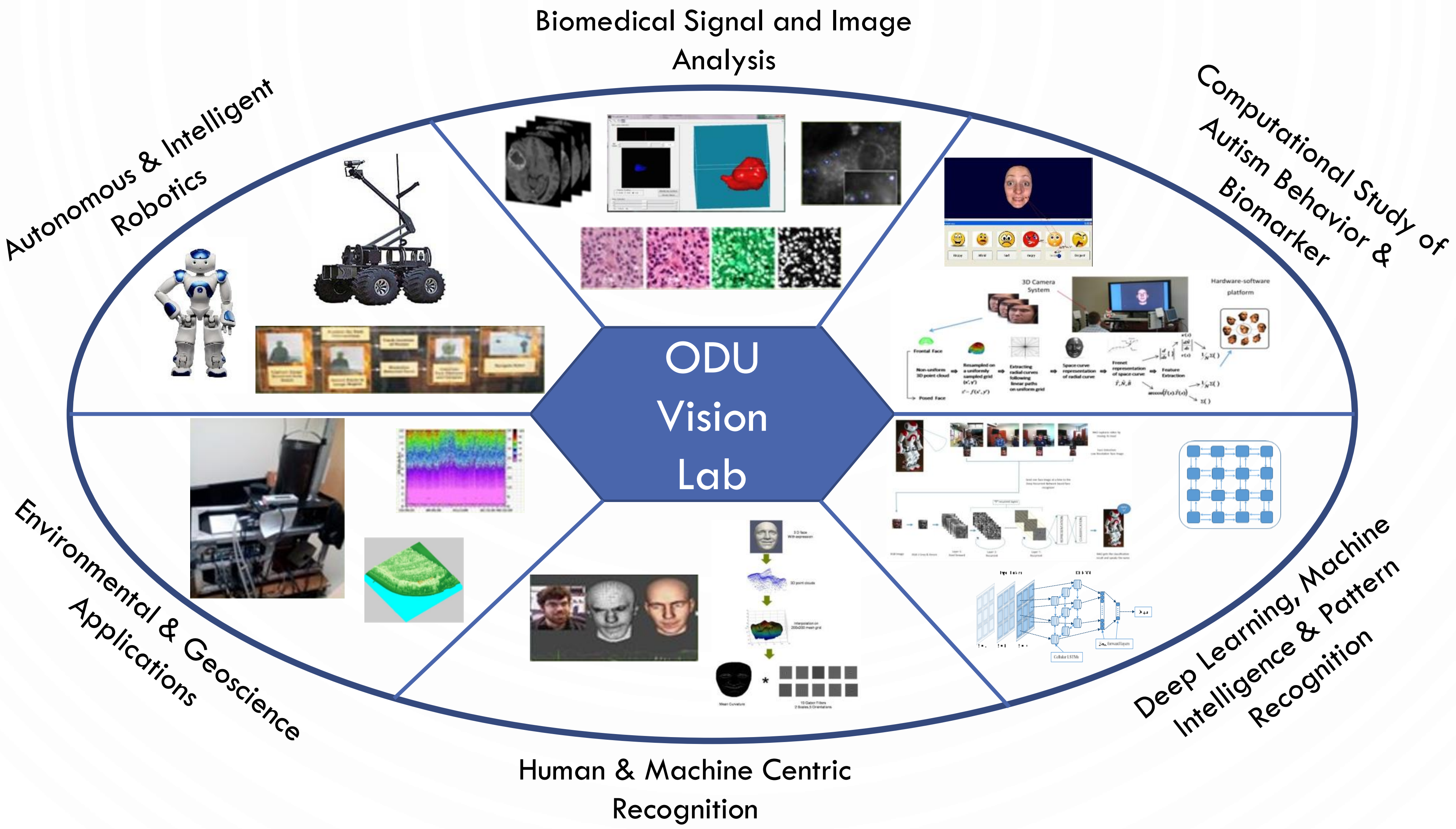
- Introduction to ODU Vision Lab
- Automated CEBAF SRF Cavity Fault Classification Project
- Introduction to time series data
  - Machine learning for time series data analysis
  - Deep Learning for time series data analysis
- Experimental Models
- Novel Deep Cellular Recurrent Learning Architecture for Multi-Sensor Signal Processing
- Results
- Conclusions and Future Work

ODU VISION LAB

- Multi-disciplinary research group
- Well-equipped
- Experience in a broad range of projects supported by NSF, NIH, NASA, DOD, DOT, and more

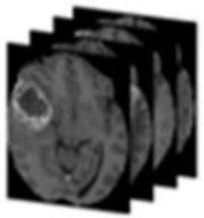
Contact: Dr. Khan M. Iftekharuddin, kiftekha@odu.edu sites.wp.odu.edu/VisionLab

ODU VISION LAB RESEARCH AREAS

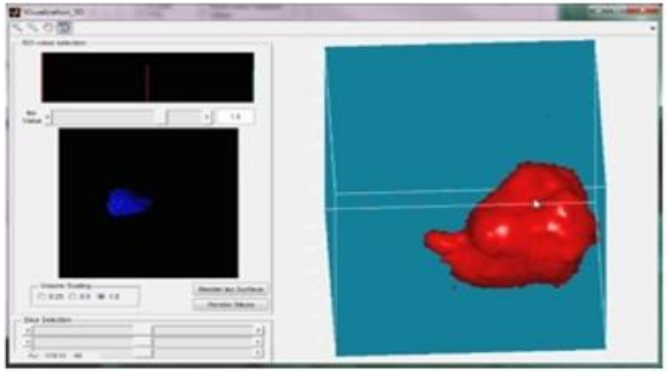


COMPUTATIONAL MODELING FOR BRAIN TUMOR SEGMENTATION AND SURVIVAL PREDICTION

- **Automatic Brain Tumor Segmentation and Classification**
  - Manual tumor segmentation is time consuming
  - Tool for automatic brain tumor segmentation
  - Placed **3^{rd}** in an **international** tumor segmentation competition, MICCAI/NIH BRATS GLOBAL CHALLENGE, 2013
  - Placed **2^{nd}** in an **international** tumor type classification competition, MICCAI/NIH RAD-PATH GLOBAL CHALLENGE, 2019
- **Automatic Survival Prediction for Patients with Brain Tumor**
  - Novel machine learning and texture based technique
  - Placed **1^{st}** in an **international** survival prediction competition, MICCAI/NIH BRATS GLOBAL CHALLENGE, 2018



MRI Volume



3D Visualization

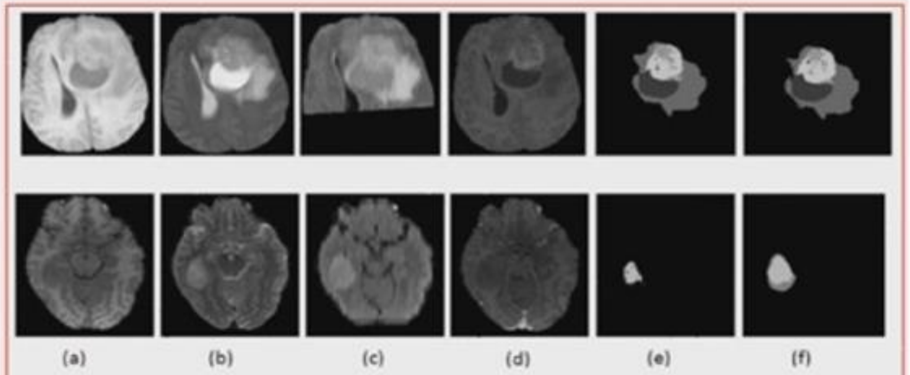


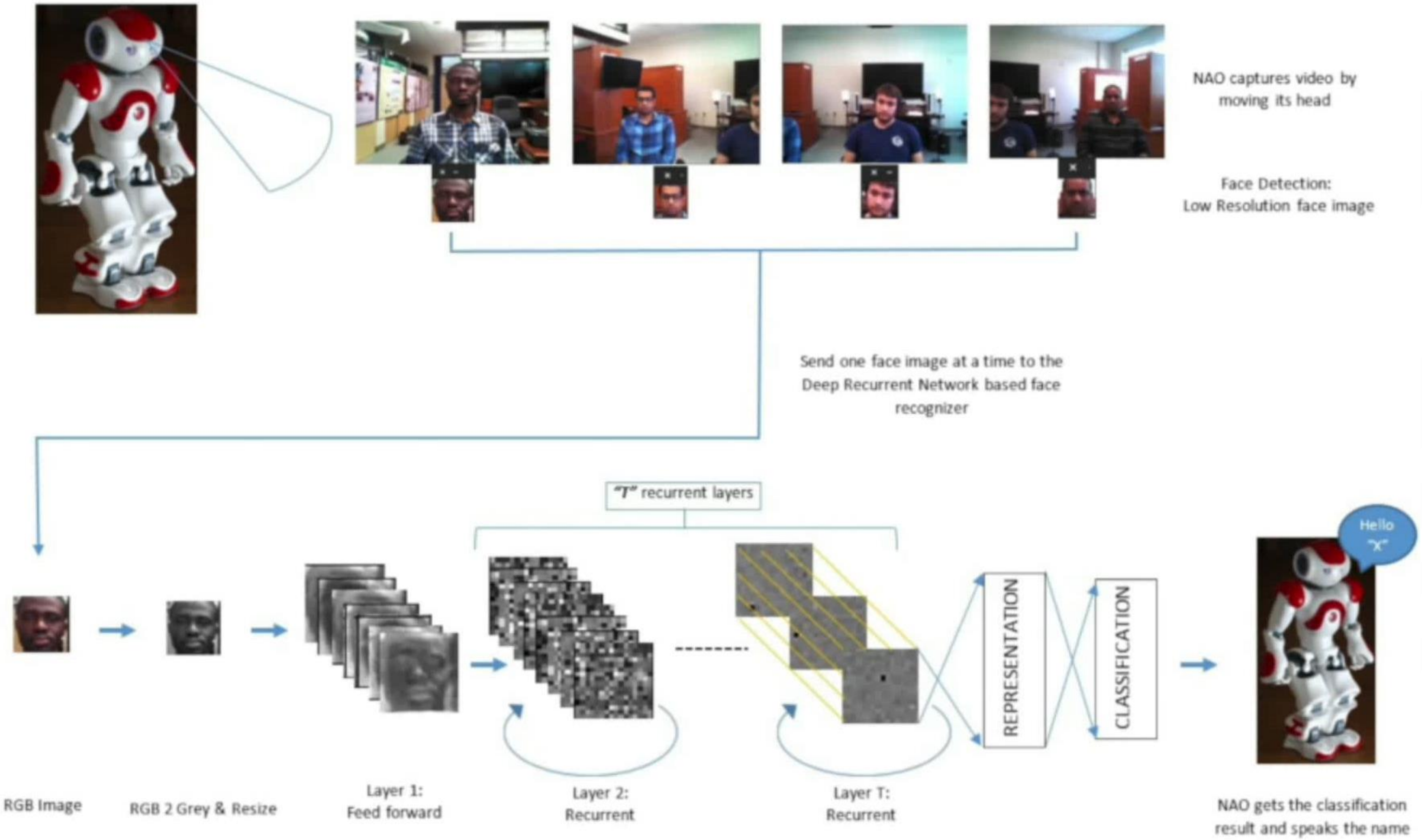
Figure 2: Segmented tissues with corresponding input and ground-truth images. Each row represents an example set of multimodality MRI slices. ; Input: (a) T1, (b) T2, (c) Flair (d) T1contrast. (e) Segmented image (f) ground-truth. Labels in the ground-truth: 1-necrosis, 2- edema, 3-non-enhancing tumor, 4- enhancing tumor, 0-everything else.

Brain tumor segmentation results

AUTONOMOUS ROBOTICS & MACHINE VISION

Biologically Inspired Vision Modeling

AI Driven Robotics

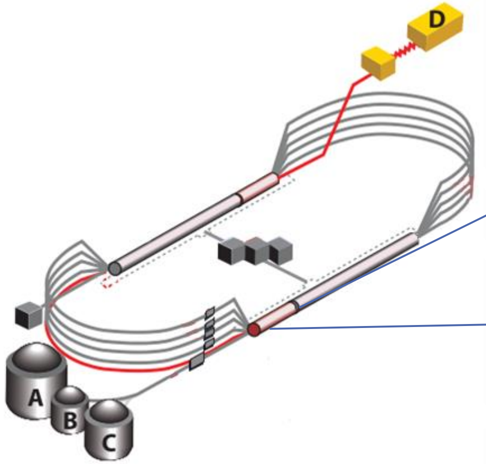


Biologically inspired deep recurrent model based real-time face recognition using humanoid robotic platform NAO

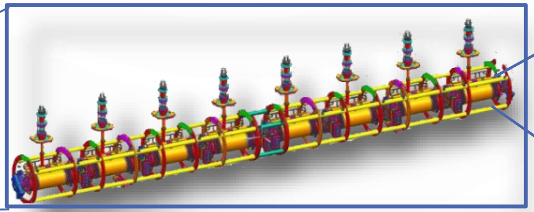
APPLICATION OF MACHINE LEARNING AND DEEP LEARNING FOR SRF CAVITY FAULT DETECTION AND CLASSIFICATION

INTRODUCTION TO CEBAF PROJECT

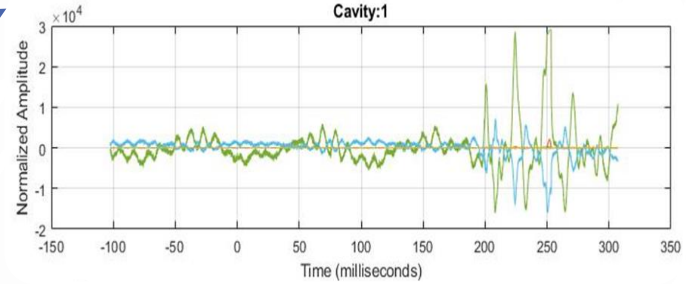
- Jefferson Lab CEBAF cavity fault classification task



Continuous Electron Beam Accelerator Facility (CEBAF)



Cryomodule with 8 SRF cavities



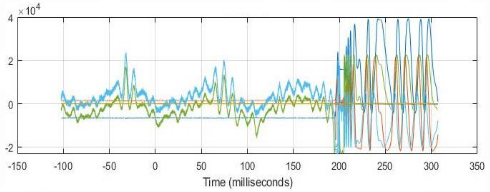
RF signal recording from cavity 1

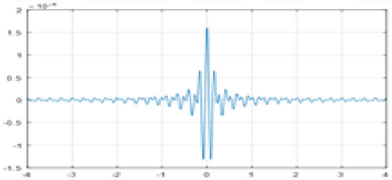
- 12 cryomodules
- 8 cavities in each cryomodule
  - Serially located

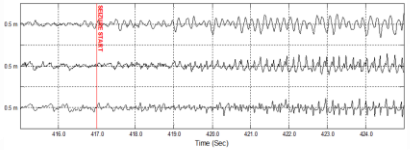
- Efficient **multi-sensor time-series** analysis task

TIME SERIES DATA

- Pattern recognition
  - Static data
    - Machine learning
    - Deep learning
  - Time series data
    - Machine learning
    - Deep recurrent learning

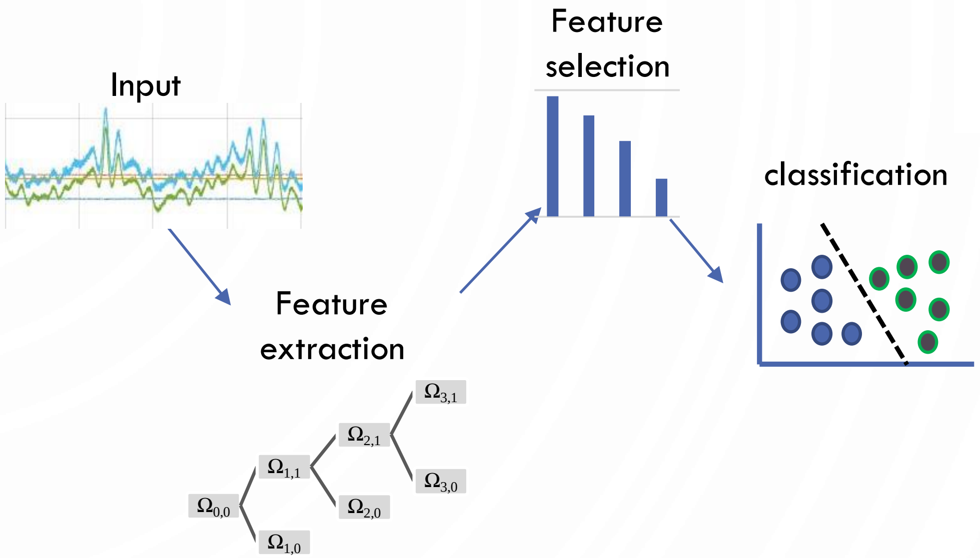




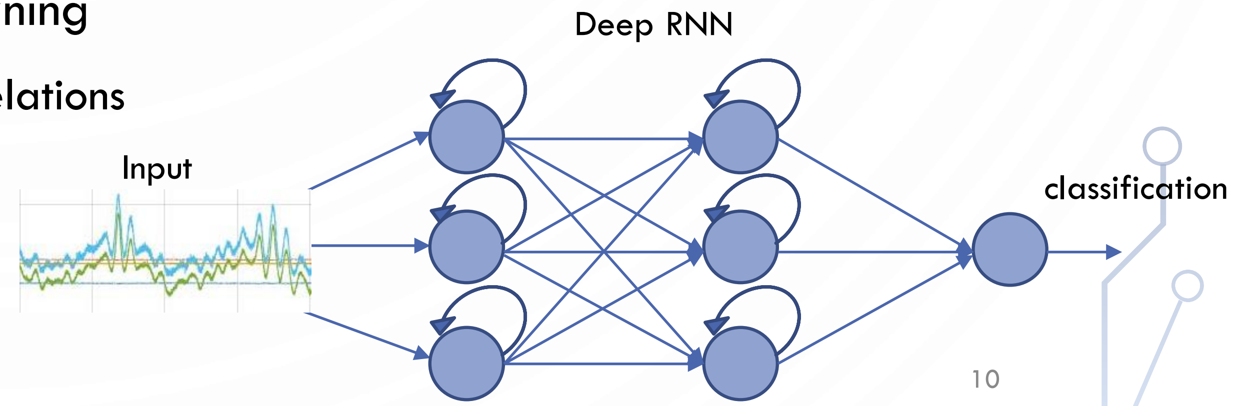


TIME-SERIES DATA ANALYSIS

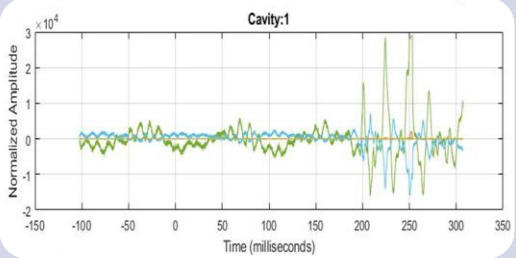
- Machine learning for time series data
  - Intermediate representation of data: features
    - Feature engineering: domain expertise
  - Captures the temporal information
    - Converts problem to a static classification task
  - Performance depends on feature quality

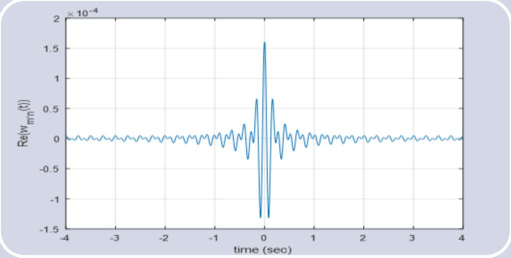


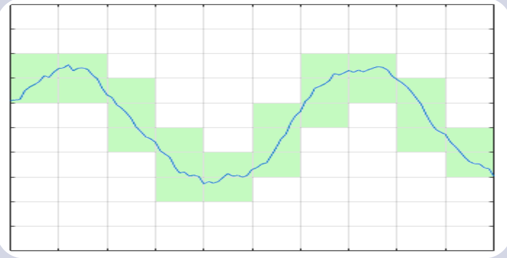
- Artificial Neural Networks (ANN) and Deep learning
  - Recurrent neural networks to process temporal relations
    - Feature learning: usually performs better
  - Can get prohibitively large for complex inputs
    - Time series with spatial information



FEATURE ENGINEERING FOR TIME SERIES DATA







Statistics of data

- Mean, variance
- Skewness, kurtosis
- Number of zero crossings
- Autoregressive coefficients

Time-frequency analysis

- Wavelet transform
- wavelet packet transform
- Filter banks

Self Similarity

- Fractal Analysis
- Box counting

FEATURE LEARNING WITH DEEP NEURAL NETWORKS

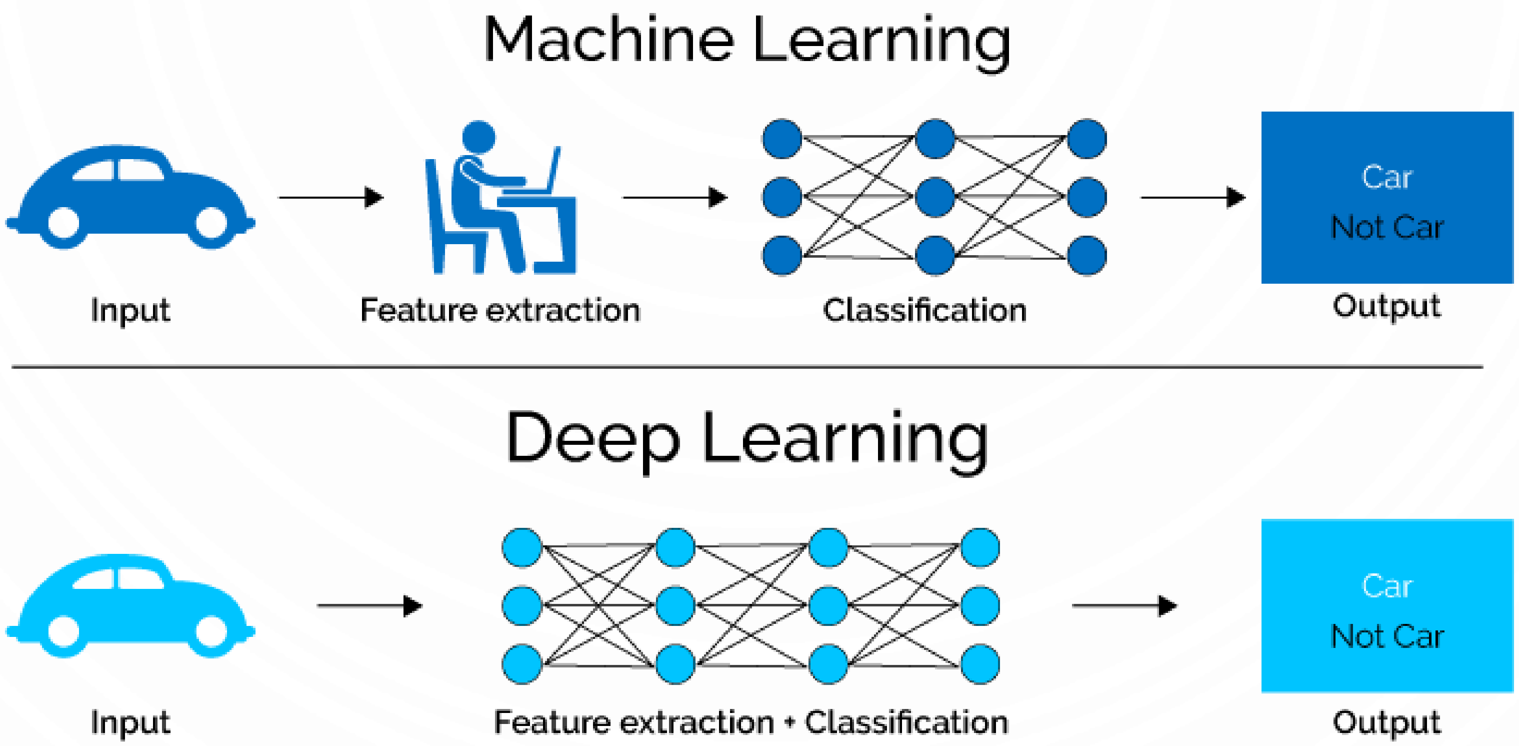
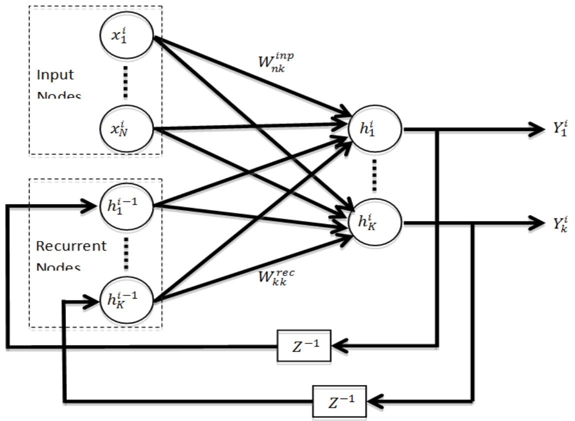


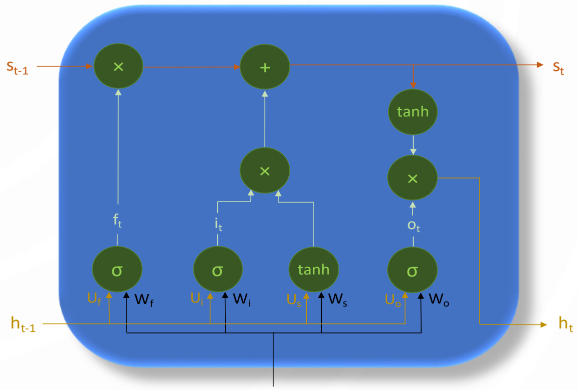
Image source: https://medium.com/datadriveninvestor/not-so-deep-learning-2c51bae54c9d

DEEP RECURRENT LEARNING

Generic Deep Recurrent Neural Network Architectures

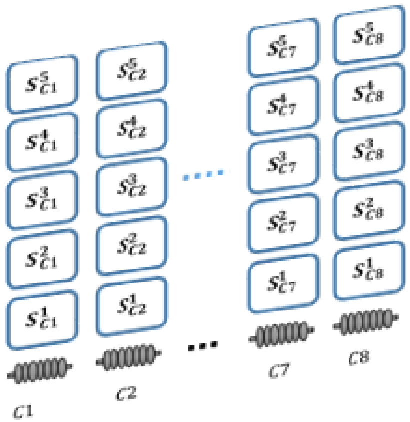


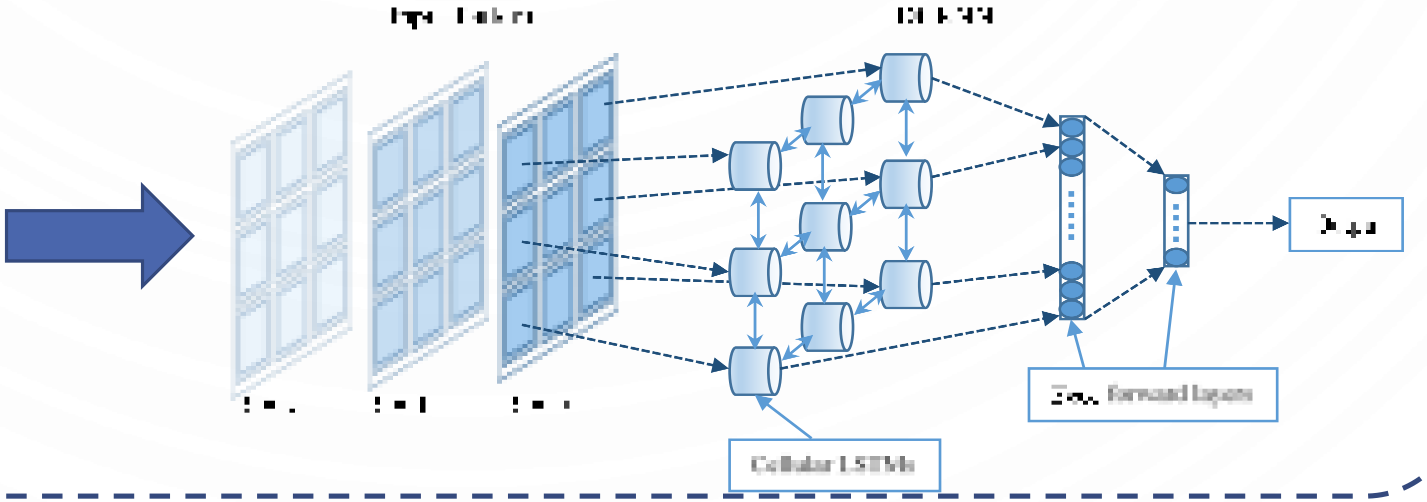
Recurrent Neural Network



Long Short-Term Memory Network

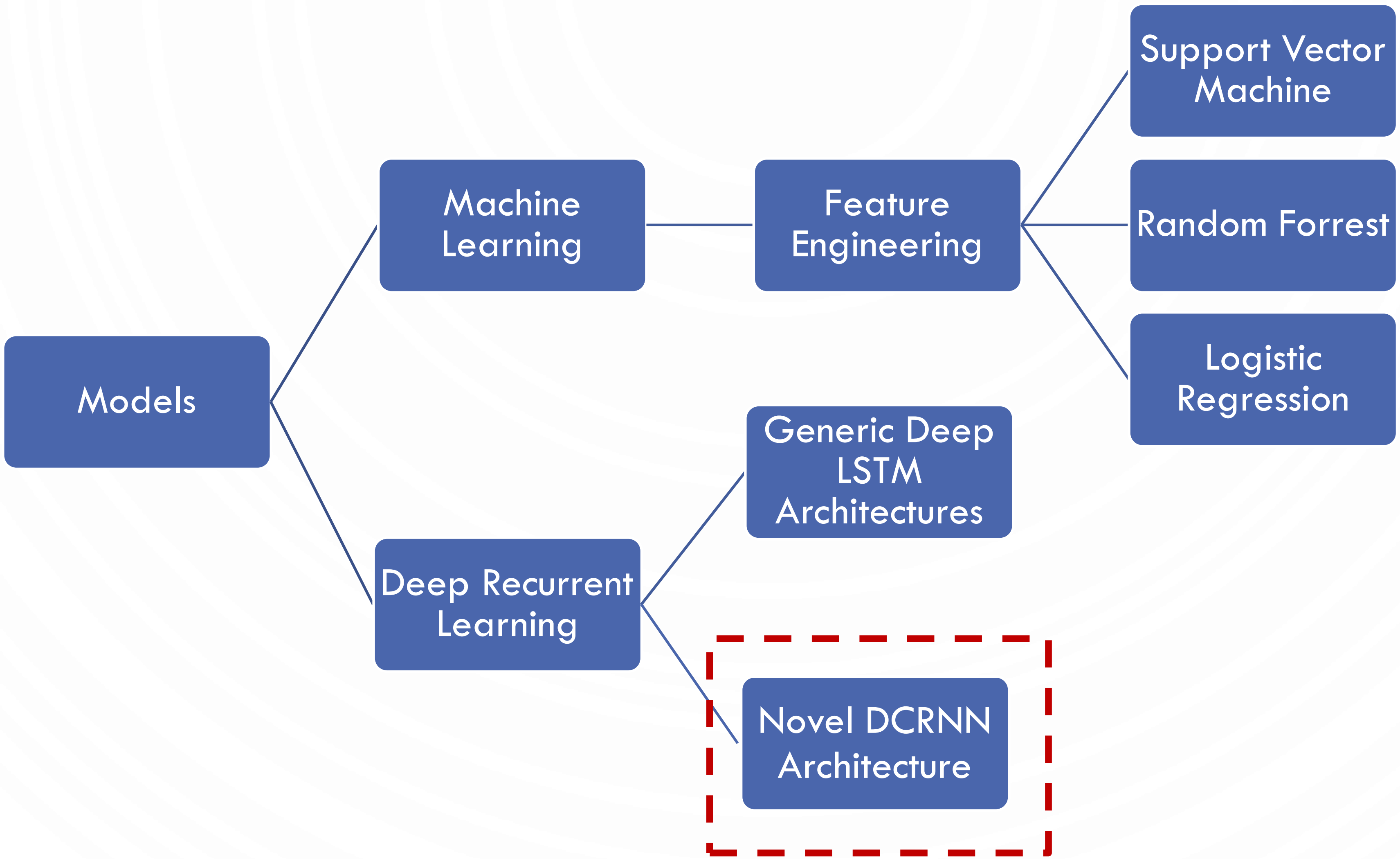
Novel Deep Cellular LSTM Neural Architecture for Multi-Sensor Data Processing





SRF Cavities & Signals

EXPERIMENTAL MODELS



SRF CAVITY FAULT CLASSIFICATION DATASET

- SRF Cavity classification dataset preparation
  - Approx. 600 samples of cavity fault data
    - Each sample contains 17 RF waveforms from each cavity
      - Choose 5 most significant RF waveforms based on analysis by expert
    - Each waveform: ~1.6 sec (8196 time samples)
    - Pre-processing: z-score normalization + down sampling
  - 5 different fault types → 5 class classification task
- Analysis procedure
  - 10-fold cross validation

SRF CAVITY FAULT CLASSIFICATION RESULTS

Methods	Number of recurrent neurons in each layer	10-fold accuracy ± standard deviation	Processing time
Feature Engineering + SVM	-	90% ± 4%	Order of Minutes
Feature Engineering +RF	-	91.5% ± 2%	Order of Minutes
Feature Engineering + LR	-	87.4% ± 4.8%	Order of Minutes
Deep LSTM	256, 256 (bidirectional)	88.83% ± 2.4%	Order of Seconds
Novel DCRNN	**5, 5 (unidirectional)**	**89.1% ± 2.7%**	Order of Seconds

CONCLUSIONS

- Preliminary analysis for automated fault classification
  - **Substantial classification performance** for all models
  - Machine Learning and Deep Learning models perform with comparable accuracy
    - DL models perform considerably faster
    - DL models promising for **real-time** use
  - Novel Deep cellular Recurrent Neural Network (DCRNN)
    - Distributed processing for multi-sensor data such as CEBAF cavity signals
    - Highly efficient use of computational resources
    - Comparable performance to other models
    - Novel contribution to DL research

FUTURE WORK

- Experimentation with larger dataset
  - Identification of new fault types
- Robust DL performance with real-time performance
  - Efficient models
- Extend deep recurrent learning models for fault **prediction**

THANK YOU!