Bayer Pressure Prediction System

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PresSURE Predictor

INTRODUCTION

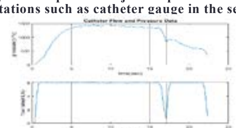
- CT Scans are common in America, with over 70 million scans per year
- Scans sometimes malfunction, exceeding maximum catheter pressure causing the technician to abort the procedure

Figure 1: Stellant CT Injection System

- There is no standard procedure for technicians to follow, rather each operator uses their own methods based on experience and unwritten rules
- Developing a way to predict a pressure given the injection conditions in clinical use to ensure the clearest and most enhanced CT images.

BACKGROUND

- No Standardization of protocols for technicians to follow
  - Configuration of injector and procedure is largely up to the technician and his/her background
- PDS (Pressure-Disarm Scenario):
  - Occurs when the pressure in an injection reaches dangerously high levels, which could harm the patient or damage the catheter
  - Causes the injection to automatically abort
- PLS (Pressure-Limiting Scenario):
  - Happens when the given setup for an injection procedure cannot reach an adequate pressure due to limitations such as catheter gauge in the setup



- We will predict maximum pressure before the injection is run using empirical and theoretical models so that the probability of PDS and PLS is significantly reduced
  - Prediction of pressure on catheter gauge, contrast properties and saline properties
- We want to prevent suboptimal scan leading to increased scan time or radiation exposure

Mathematical Model Results

- Goal is to predict the maximum pressure an injection will reach within 5% of the actual value
- Program consists of three segments: Data Parser, Nonlinear Analyzer, Output GUI
  - The data parser splits the large amount of data into chunks based on factors such as catheter gauge, saline type, and contrast type
  - The nonlinear analyzer uses nonlinear least squares regression to compare the model to empirical pressure vs. time data
  - The output GUI indicates a predicted waveform to the technician and predicts the maximum pressure as well as whether the injection should continue
- Results - Used three different models with varying accuracy:
  - Logistics function was not very effective, not capturing outliers
  - Models using Hagen-Poiseuille equation did not capture the correct shape
  - Only successful model was a step with a first-order lowpass filter had sub-5% error (roughly 80% of the time)

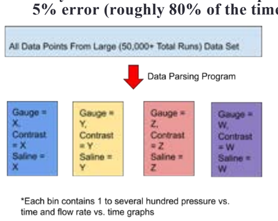


Figure 2: Data parser sorts the data set into buckets grouped by contrast type, saline type, and catheter gauge

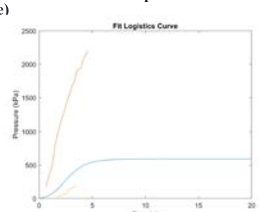
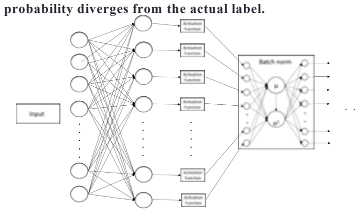


Figure 3: Logistics Model Failed to capture outliers, step model (pictured in GUI) worked better.

DLNN Model

1. Classification Based Model
   - Classifies the pressure into buckets within a range of 20 kPa based on the protocol settings
2. Regression Based Model
   - Estimates a singular pressure value in kPa based on the protocol settings.
3. Loss Functions
   - Input: Types of Phases, Volume of Phases, and Flowrate of Phases
   - CrossEntropyLoss: Cross-entropy loss, or log loss, measures the performance of a classification model whose output is a probability value between 0 and 1. Cross-entropy loss increases as the predicted probability diverges from the actual label.
   - L1 Loss: $S = \sum_{i=1}^{n} |y_i - f(x_i)|.$
   - L2 Loss: $S = \sum_{i=1}^{n} (y_i - f(x_i))^2$



4. Architecture – Multiple Layers
   - Input: Types of Phases, Volume of Phases, and Flowrate of Phases
   - Linear Layer: Linear combination on the inputs plus a bias
   - Activation Function: Compute whether neuron should be fired based on input; provides non-linearity
   - Batch Normalization: Standardizes the inputs to a layer
5. Results:
   - Classification: Accuracy of 94.8% and a Loss of 0.4 was achieved with CrossEntropyLoss
   - Regression: Accuracy shows pressure shift in the graph from 0% to 46% in the 0 – 0.5 range and a Loss of 5 was achieved with L1 Loss.

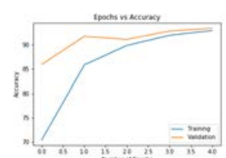


Figure 4: Epoch vs. Accuracy for the Classification Model; Validation accuracy increases with training.

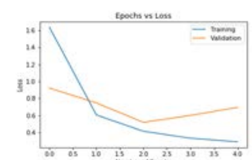


Figure 5: Epoch vs. Loss for the Classification Model; Validation loss increases with Training; No overfitting.

Figure 6: Epoch vs. Accuracy for the Regression Model; Represents deviation from True value

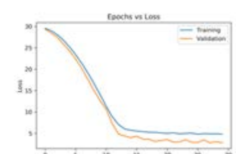


Figure 7: Epoch vs. Loss for the Regression Model; Validation loss increases with Training; No overfitting

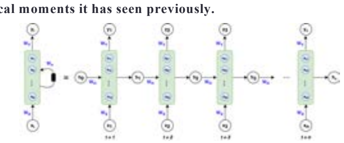
Considerations for Further Development

1. Regulatory
   - Due to informative nature: follow *Non-Device* Clinical Decision Support guidance
2. Reimbursement
   - Existing payment codes for injection procedures still apply: A9698, Q9958-65
3. Intellectual Property
   - Patentable *method* (incl. technician input, displaying output); no similar existing prior art
4. Costs of Production
   - Amortized per Stellant injector: cost ≈ cost of upgrades needed to integrate our software

Conclusions

1. Mathematical Model
   - Model can produce a graph for the technologists but is ineffective and inaccurate to be able to be used in the Stellant device.
2. Deep Learning Model
   - Our model is effectively and accurately able to determine the maximum pressure but is unable to create a continuous graph for the technologists.

- Future Work
  - Recurrent Based Model – Change Data
    - Proper pressure output at the current time depends not only on current settings, but also past scenes and their change/trend.
    - We need the pressure to respond to current input, while remembering critical moments it has seen previously.



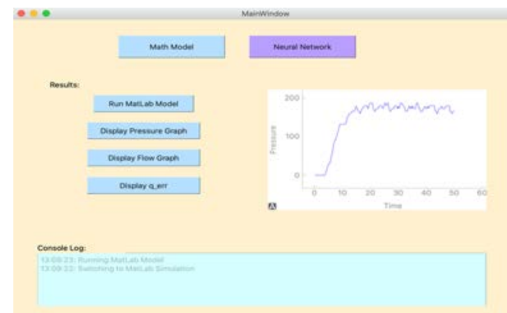


Figure 8: Left: Prototype GUI. Runs the mathematical model using the MATLAB engine and displays the output in Python GUI can also use the DLNN to predict maximum pressure.

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