Predictive Maintenance for Wireless Access Equipment Using Image Data at TELUS

Objective: To be able to use image data from mobile network sites to predict potential equipment failures and maintenance needs.

At TELUS, we have developed Machine Learning (ML) models to analyze images taken from our network sites to be able to provide status and prediction of equipment condition. This is currently done in four (4) stages:
The existing model provides benefits with reducing network downtime by predicting equipment failures before they occur, but with high false positives and false negatives which leads to imperfect predictions.

Section 1:

▪ **Problem statement:**

Contribution of varying environmental conditions, lighting, and obstructions to high false positives and false negatives.

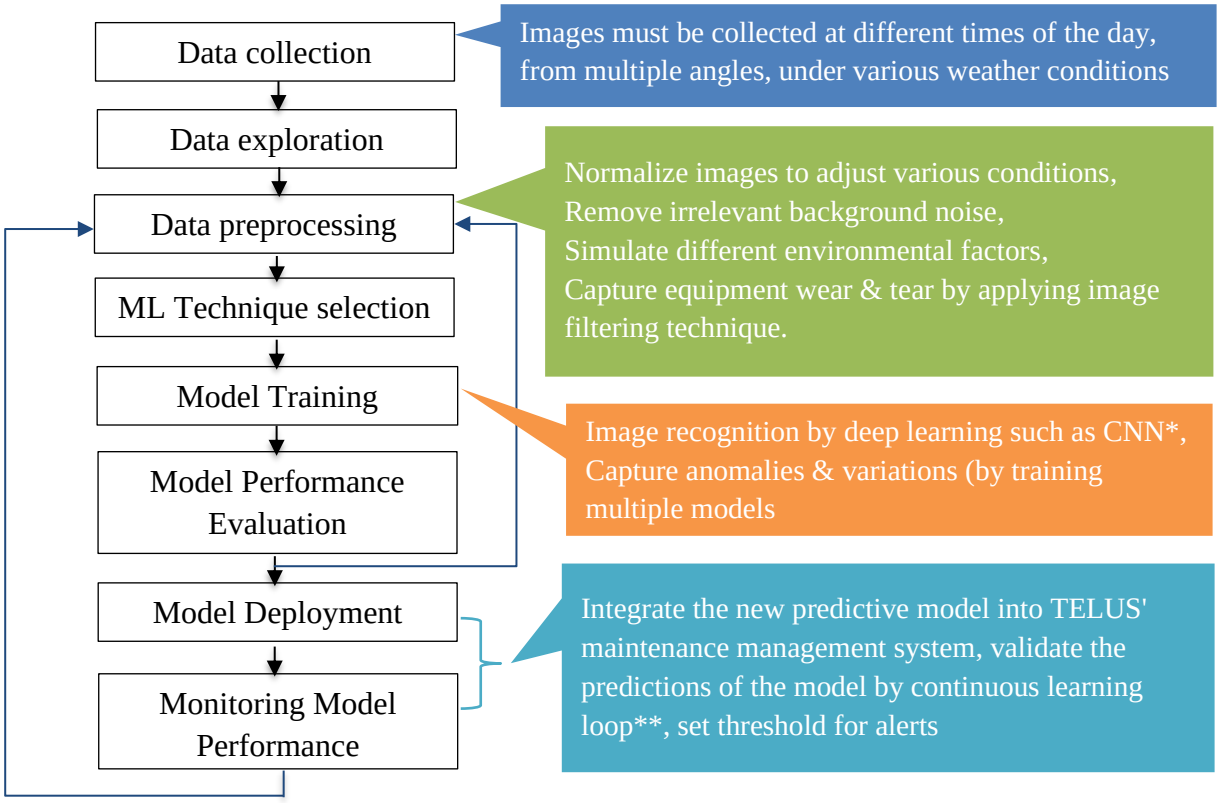
▪ **Consequences of Solving vs. Maintaining Status Quo**

a. If Solved:
   - Cost Savings: Improved predictive maintenance for network hardware – improved forecast when network hardware components might fail, enabling proactive maintenance and minimizing downtime.
   - Improved network reliability, cost savings

b. If Status Quo Maintained:
   - Frequent Failures: Incorrect images can lead to unexpected equipment failure
   - Higher Costs: Missed out predictions on equipment failure will lead to emergency call-outs of technicians which is more expensive than scheduled maintenance.
   - Network unavailability: Unpredicted equipment failure might result in urgent hardware replacement which is difficult to arrange if not in the warehouse.
   - Customer Dissatisfaction and churn: Unpredictable failures can lead to poor customer experiences and increased churn

Section 2:

My **proposed solution** in an eight (8) steps workflow:



** CNN (Convolutional Neural Network): I suggest using CNN which is a deep learning technique, used in image recognition tasks.*

*** Continuous learning loop: The predictions made by the ML model will be validated by the site technicians. They will take new images which will be used to retrain the ML model to correct labels. This should reduce false positives/ negatives.*

Relevant techniques:

Data Collection:	**Preprocessing**	**Model Training**	**Integration/ Deployment**
• Data augmentation	• Noise reduction • Contrast enhancement • Edge detection • Data Augmentation	• Transfer learning • ResNet50 • Fine tuning • Hyperparameter tuning • cross-validation	• Continuous data validation & adjustment

Section 3:

To quantify the impact of my proposed solution, I would like to consider the following **assumptions** based on my experience working with the Network Operations team:

- Average equipment failure rate is every six (6) months;
- 5% improvement in reliability results in 2% increase in customer retention;
- Some of the hardware failures are critical and results into downtime which leads to loss of revenue.

Impact Quantification:

- **Reduced false positives/ negatives:** Implication of preprocessing and transfer learning will help reduce the false positives/ negatives by 10-20%.
- **Reduced Downtime:** Higher accuracy in prediction will reduce hardware failures by up to 10-15%. We will be able to reduce maintenance costs and loss of revenue by 10-15%.
- **Reduced Operations & Maintenance costs:** TELUS' network operations team can optimize their preventive maintenance schedule which will reduce urgent repairs, resulting into decrease in maintenance costs by 15-20%.
- **Higher customer retention and lower churn rate:** Higher network reliability will provide our valued customers with better experience; which will result into higher retention and lower churn, and increased revenue by 4-8%.

Section 4:

My high-level implementation plan starts with having a conversation with the Network Operations Manager, followed by a formal meeting to share my analysis on improving the existing predictive models that uses images captured by Network technicians.

Data collection method:

The key here is to have clear images and robust data taken at various times of the day, under varying weather conditions. A detailed schedule would be required.

- Field technicians will capture images as part of site inspection checklist. Images must contain equipment labels (serial number, part number), wear and tear such as leaks, cracks, corrosion, dust accumulation etc.
- The image capturing schedule must consider different environmental conditions to ensure robustness of the data.

Type of data required:

- High-resolution images of hardware, cable joints, battery joints and obstructions in front of antennas.
- Environmental data
- Time since last maintenance

Data preprocessing:

- Contrast normalization, Image Segmentation, data augmentation will help reduce environmental impact to the images.

Type of Modeling required:

- Transfer Learning with ResNet50 as pre-trained model.
- CNN model that will use filters on it so that it learns to do object detection, image segmentation and classification.
- I would also apply ‘Embedding’ technique that I learned in the NLP session here for image embedding.

- Several models to be trained using different architectures (e.g., ResNet50, VGG16, InceptionV3).
- Grid Search to identify the optimal hyperparameter.

Model measurement/ evaluation:

- I would use Precision, Recall and F1-score to assess false positive and false negative amounts/ rates.
- 'Prompt Engineering' to reduce nuances and for text response from the model.

Model Selection:

- I would select the model with highest F1 score as this is the harmonic mean of Precision and Recall.
- Model with the best hyperparameters (found by Grid Search).

Finally, the primary condition to have this adjusted model work is proper data collection by the field technicians. That should then be followed by implications of the preprocessing of the images, building the ML models and integrating it into the TELUS' maintenance management system. I hope I will be able to convince TEUS' senior leadership team based on my analysis. If I do, the result will definitely be positive in terms of increased revenue, lower maintenance cost and higher customer satisfaction.

References:

1. TELUS Network Quality Assurance process
2. TELUS Network Maintenance Dispatch process
3. TELUS RAN Machine Learning Model applications
4. MMA 865 class lectures.