**Department of Computer Science**
**St. Francis Xavier University**

**M.Sc. Thesis Proposal Presentation**

# Sample-Based Error Rate Assessment Through Predictive Confidence in Biomedical Applications

**Presented by**
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**Date:** May 15th, 2025
**Time:** 11:00 AM – 12:00 PM (Atlantic Time, CA)
**Location:** Online via Microsoft Teams
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Predictive confidence is essential for evaluating the reliability of machine learning models in medical diagnosis. However, many traditional techniques do not consider differences in error rates on a per sample basis, thus not providing meaningful adaptive error rate estimations for each individual predictive sample. This is especially important in health care settings, where any prediction is critical. These issues are often created by sampling biases in data and the inherent randomness of machine learning algorithms, making some predictions less reliable.

In this work, we propose a sample-based error rate estimation framework that enhances predictive reliability by integrating multiple machine learning and deep learning algorithms, including logistic regression, stochastic gradient descent, convolutional neural networks, random forests, and light gradient boosting machine. Our method utilizes confidence scores from individual base models to assess the relationship between predicted confidence and error rate. The framework was evaluated in the MedMNIST v2 dataset, where the results indicate a strong correlation between predictive confidence and observed error rates.

These findings validate the effectiveness of our sample-wise error rate assessment approach. We will further refine our ensemble adaptive learning algorithms and extend our analysis to regression tasks, aiming to enhance prediction quality while reducing errors and ensuring more systematic error patterns. By dynamically adjusting the model's reported error at the predictive sample level, our approach offers a more robust and reliable framework to support medical decision making.