NEURAL INFORMATION PROCESSING SYSTEMS

WiML Workshop @ NeurIPS 2024

Mitigating Feature Bias in DL Models for Cervical Cytology

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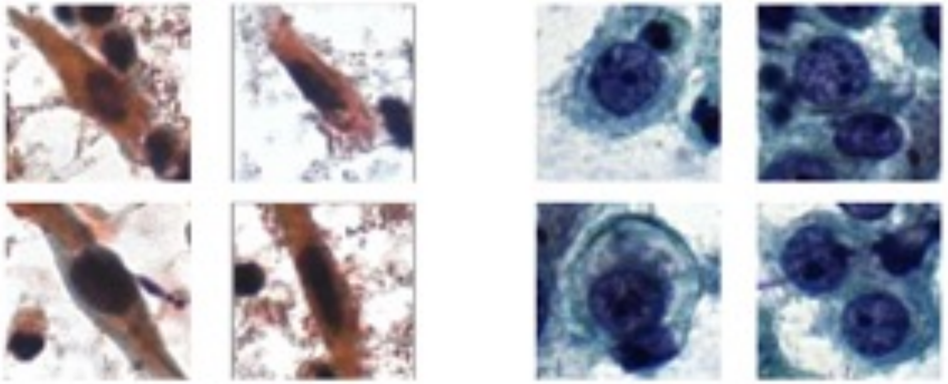
Motivation

- Clinical datasets often contain inherent feature biases can hinder the practical deployment of these DL models.

- Feature Bias refers to **uneven representation of features within same class, leading to inconsistent model performance.**

- We **introduce an sampling-based feature-bias mitigation method** to reduce model skewness and improve performance across feature cohorts.



Sample Images of various features in Squamous Cell Carcinoma (SCC) class

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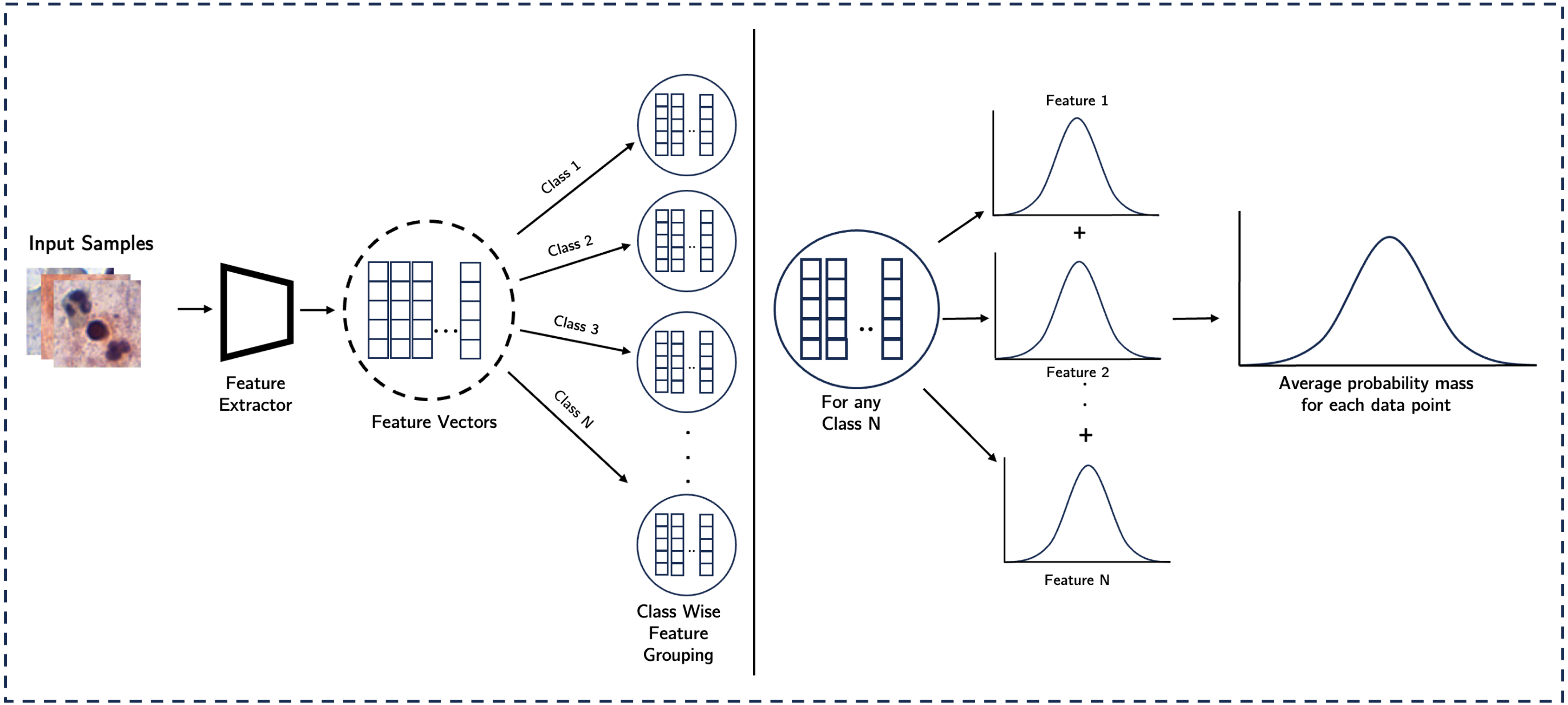
Our Approach



- <u>Common Workflow for Bias Agnostic & Bias Mitigating Approach</u> :

  Feature Extraction & Segregation -> Probability Distribution Computation -> Avg. Probability Mass Calculation -> Data Pt Categorization

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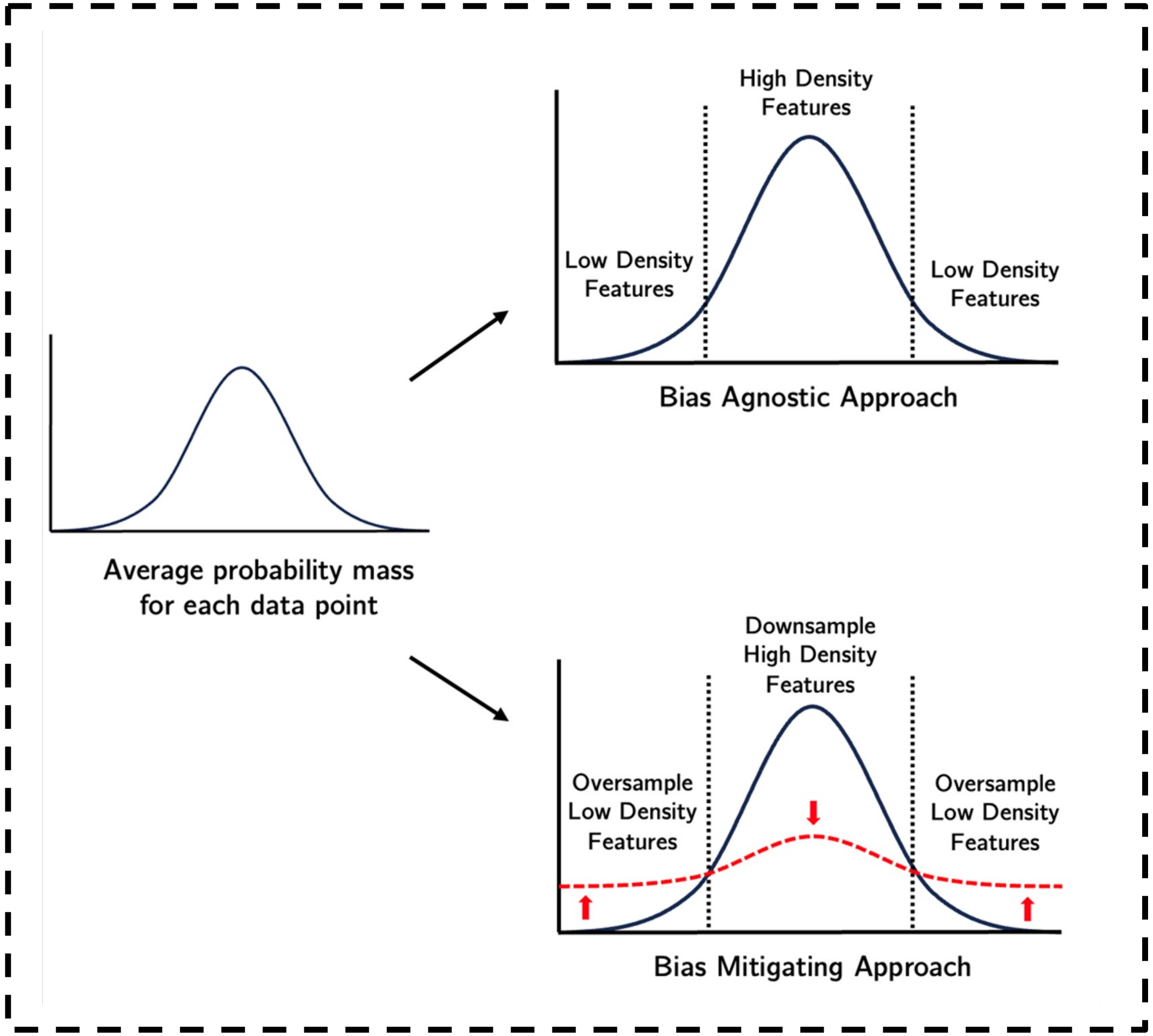
Our Approach



Bias Agnostic vs Bias Mitigating Approach

→ Randomly sampled data points → predominantly signal from high-density features to classifier.

→ Oversamples (⬆) low density features & under samples (⬇) high density features → balanced signal to the classifier

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Methodology

- **Setup**: We compare this bias mitigation method to a common bias agnostic apporoach and compare their effectiveness.

- **Performance Metric** : AUC with 5-Fold Validation

- **Model Used**: DieT

- **Datasets**: CRIC cervical cell classification dataset

Results

	Low Density Cohort (in %)	High Density Cohort (in %)
Bias-Agnostic	$73.89_{\pm 0.33}$	$78.97_{\pm 0.32}$
Bias-Mitigating	$\mathbf{77.38}_{\pm 0.59}$	$\mathbf{78.73}_{\pm 0.77}$

- **Bias-Agnostic approach** yields an **AUC difference of 5.08%** between the two cohorts representing a **73.42% reduction in the AUC difference** compared to the Bias-Agnostic approach.

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Summary

1. **Feature Bias mitigation is important** for medical settings.

2. An effective bias-mitigating approach **reduces the skewness in the model performance** across various feature cohorts.

3. Our bias mitigation approach can mitigates performance gaps between density cohorts, **leading to equitable and robust outcomes in medical applications.**