

# **Aditya Narendra's Portfolio**

MS in Computer Science and Engineering

Fall 2026

# Publications

# Towards Reliable Few-Shot Adaptation of Pathology Foundation Models via Conformal Prediction

**Aditya Narendra<sup>1</sup>, Subhankar Panda<sup>1,2</sup>, Chandresh Kumar Maurya<sup>1</sup>**

<sup>1</sup> Department of Computer Science and Engineering, IIT Indore, India

<sup>2</sup> Odisha University of Technology and Research, India

{adityanarendra, chandresh}@iiti.ac.in

subhankarpanda556@gmail.com

**Venue:** AIMedHealth Bridge Program, AAI 2026

## **Abstract:**

Recent advances in foundation models have enabled their integration into high-stakes clinical settings, particularly in computational pathology, where domain-specialized FMs demonstrate strong generalization. However, real-world deployment is constrained by their poorly calibrated uncertainty awareness and degraded performance in low-data regimes requiring few-shot adaptation strategies, leading to unreliable and inefficient diagnostic workflows. Conformal Prediction (CP) is an uncertainty quantification framework that offers distribution-free, finite-sample coverage guarantees for ensuring safer deployment in such settings. In this work, we explore the integration of various CP methods with pathology foundation models using three few-shot adaption strategies for classification tasks across two datasets. To assess the clinical effectiveness of these approaches, we propose four novel metrics aimed at improving clinical reliability and alleviating diagnostic workload in few-shot settings. Our results demonstrate that Conformal Prediction methods enhance the reliability of pathology foundation models and offer actionable uncertainty estimates to enable safe and efficient deployment in few-shot pathological classification workflows, with the LAC method achieving the best overall performance.

**Keywords:** Conformal Prediction, Few-Shot Classification, Pathology Foundation Models, Uncertainty Quantification

[\[Link to Full Paper\]](#) || [\[Paper Website\]](#) || [\[Code\]](#)

# Ensuring Class-Conditional Coverage for Pathological Workflows (Student Abstract)

**Siddharth Narendra<sup>1</sup>, Shubham Ojha<sup>2</sup>, Aditya Narendra<sup>2</sup>,  
Abhay Kshirsagar<sup>3</sup>, Abhisek Mallick<sup>4</sup>**

<sup>1</sup> Odisha University of Technology and Research, Bhubaneswar-751029, India

<sup>2</sup> Cincinnati Children's Hospital Medical Center

<sup>3</sup> University of Illinois Urbana-Champaign

<sup>4</sup> Northeastern University

{siddharthnarendra0708, shubham.ojha1000, adinarendra0108}@gmail.com  
abhaysk2@illinois.edu, mallick.ab@northeastern.edu

**Venue:** AAAI 2025

## **Abstract:**

Conformal Prediction (CP) is an uncertainty quantification framework that provides prediction sets with a user-specified probability to include the true class in the prediction set. This guarantee on the user-specified probability is known as marginal coverage. Marginal coverage refers to the probability that the true label is included in the prediction set, averaged over all test samples. However, this can lead to inconsistent coverage across different classes, constraining its suitability for high-stakes applications such as pathological workflows. This study implements a Classwise CP method applied to two cancer datasets to achieve class-conditional coverage which ensures that each class has a user-specified probability of being included in the prediction set when it is the true label. Our results demonstrate the effectiveness of this approach through a significant reduction in the average class coverage gap compared to the Baseline CP method.

**Keywords:** Conformal Prediction, Digital Pathology, Uncertainty Quantification

[\[Link to Full Paper\]](#) || [\[Paper Website\]](#) || [\[Code\]](#)

---

# Mitigating Feature Bias in DL Models for Cervical Cytology

---

**Subhashree Sahu**

Department of Electronics Engineering  
Silicon University  
Bhubaneswar, India

**Shubham Ojha**

Division of Biomedical Informatics  
Cincinnati Children's Hospital Medical Center  
Cincinnati OH 45229

**Aditya Narendra**

Division of Biomedical Informatics  
Cincinnati Children's Hospital Medical Center  
Cincinnati OH 45229

**Venue:** WIML Workshop, NeurIPS 2024

## **Abstract:**

Cervical cancer poses a serious health risk to women all across the world. The advancements in deep learning (DL), have driven the rise of DL-assisted cervical cytology screening methods for various diagnostic tasks. However, most of these DL approaches are susceptible to the inherent bias in clinical datasets, which restricts their practical deployment. A key source of bias in DL-based cervical cytology workflows is the high variability in the representation of various features extracted by these models across different classes. This imbalanced feature representation results in inconsistent model performance across different feature cohorts, which is known as feature bias. Building on this understanding, our work underscores the importance of mitigating feature bias in DL-based cervical cytology workflows. We demonstrate that effective bias mitigation reduces skewness in performance metrics, which improves diagnostic performance and enhances patient outcomes.

**Keywords:** Bias Mitigation, Digital Pathology, Trustworthy ML

[\[Link to Full Paper\]](#) || [\[Paper Website\]](#) || [\[Code\]](#)

# Uncertainty Quantification in DL Models for Cervical Cytology

**Shubham Ojha**<sup>1</sup>

SHUBHAM.OJHA@IHUB-DATA.IIIT.AC.IN

<sup>1</sup> *IHub-Data, International Institute of Information Technology, Hyderabad, India*

**Aditya Narendra**<sup>2</sup>

ADINARENDRA0108@GMAIL.COM

<sup>2</sup> *Independent Contributor*

**Editors:** Accepted for publication at MIDL 2024

**Venue:** MIDL 2024

**Abstract:**

Deep Learning (DL) has demonstrated significant promise in digital pathological applications both histopathology and cytopathology. However, the majority of these works primarily concentrate on evaluating the general performance of the models and overlook the crucial requirement for uncertainty quantification which is necessary for real-world clinical application. In this study, we examine the change in predictive performance and the identification of mispredictions through the incorporation of uncertainty estimates for DL-based Cervical cancer classification. Specifically, we evaluate the efficacy of three methods—Monte Carlo(MC) Dropout, Ensemble Method, and Test Time Augmentation(TTA) using three metrics: variance, entropy, and sample mean uncertainty. The results demonstrate that integrating uncertainty estimates improves the model's predictive capacity in high-confidence regions, while also serving as an indicator for the model's mispredictions in low-confidence regions.

**Keywords:** Uncertainty Estimation, Digital Cytopathology, Trustworthy ML

[\[Link to Full Paper\]](#) || [\[Paper Website\]](#) || [\[Code\]](#)

---

# Optimizing Conformal Prediction Sets for Pathological Image Classification

---

**Shubham Ojha\***

Division of Biomedical Informatics  
Cincinnati Children's Hospital Medical Center  
Cincinnati OH 45229  
shubham.ojha1000@gmail.com

**Aditya Narendra\***

Division of Biomedical Informatics  
Cincinnati Children's Hospital Medical Center  
Cincinnati OH 45229  
adinarendra0108@gmail.com

**Abhay Kshirsagar**

Dept. of Chemical and Biomolecular Engineering  
University of Illinois Urbana-Champaign  
Champaign IL  
abhaysk2@illinois.edu

**Shyam Sundar Debsarkar**

Dept. of Pediatrics, College of Medicine  
University of Cincinnati  
Cincinnati OH 45257  
debsarss@mail.uc.edu

**Surya Prasath**

Division of Biomedical Informatics  
Cincinnati Children's Hospital Medical Center  
Cincinnati OH 45229  
surya.prasath@cchmc.org

**Venue:** Pattern Recognition, 2025 (Under Review)

## Abstract:

The intersection of Deep Learning (DL) and pathology has gained significant attention, encompassing cell classification, detection, segmentation, and whole-slide image (WSI) analysis. Further works at this intersection have increasingly focused on integrating uncertainty quantification (UQ) with DL methods for pathology to address their occasional unreliability in clinical settings. Conformal Prediction (CP) is one of the UQ methods deployed for various settings, including pathology. CP methods are computationally efficient and generate prediction sets to include the true label with a user-defined coverage guarantee. However, CP methods lack inherent control over the compositionality of prediction sets, which restricts their clinical utility. This study presents a novel training method using Hinge loss for the underlying models used in CP methods. This approach aims to provide effective control over the compositionality of prediction sets, aligning more closely with the specific needs of pathologists. We evaluate the effectiveness of this training approach using three application specific metrics tailored to enhance the integration of CP methods into clinical pathology workflows. Our results show that the Hinge loss based training approach outperforms the traditional Cross Entropy training method across all evaluation metrics, leading to effective management of the compositionality of prediction sets.

**Keywords:** Conformal Prediction, Digital Pathology, Uncertainty Quantification, Human-AI Collaboration

[\[Link to Full Paper\]](#) || [\[Code\]](#)

# UrHiOdSynth: A Multilingual Synthetic Corpus for Speech-to-Speech Translation in Low-Resource Indic Languages

**Anonymous ACL submission**

**Venue:** LoResLM Workshop, EACL-2026 (Under Review)

**Abstract:**

Speech-to-Speech Translation (S2ST) focuses on generating spoken output in a target language directly from spoken input in a source language. Despite progress in S2ST modelling, low-resource Indic languages remain poorly supported, primarily because large-scale parallel speech corpora are unavailable. We present UrHiOdSynth, a three-language parallel S2ST dataset containing approximately 75 hours of speech across Urdu, Hindi, and Odia. The corpus consists of 10,735 aligned sentence triplets, with an average utterance length of 8.45 seconds. To our knowledge, UrHiOdSynth represents the largest multi-domain resource offering aligned speech and text for S2ST in this language context. Beyond speech-to-speech translation, the dataset supports tasks such as automatic speech recognition, speech-to-text translation, text-to-speech synthesis, and machine translation. This flexibility enables the training of unified multilingual models, particularly for low-resource Indic languages.

**Keywords:** Parallel Speech Corpus, Low-Resource Speech Translation, Speech-to-Speech Translation

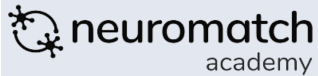
[\[Link to Full Paper\]](#) || [\[Code\]](#)



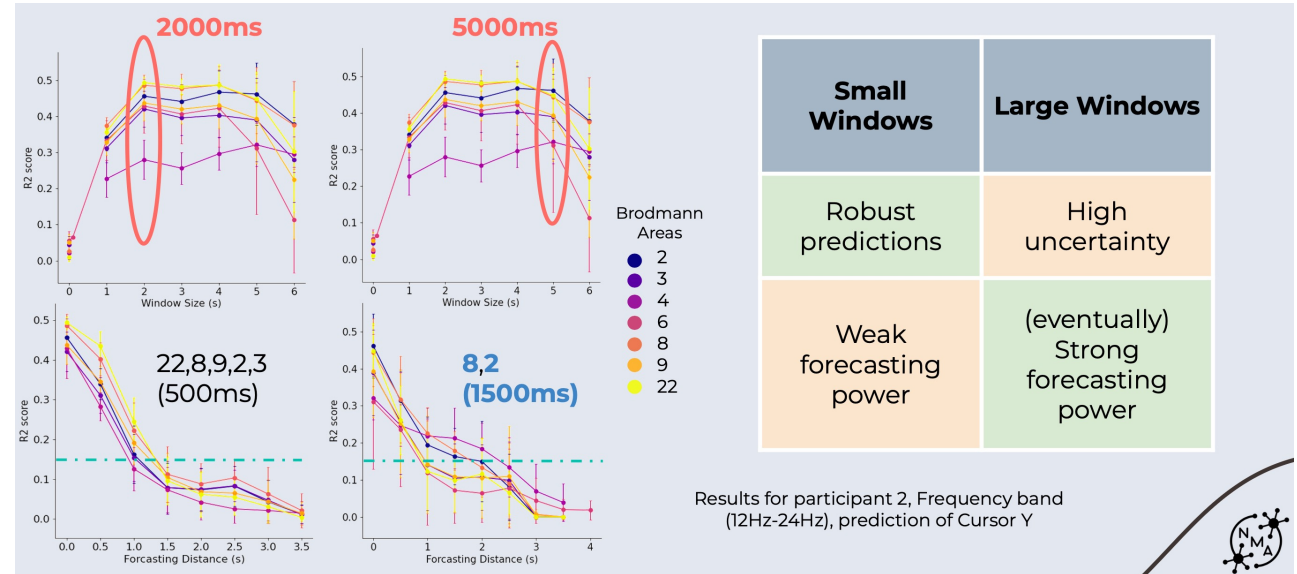
# Relevant Projects

# Prediction of Future Continuous Motion States from ECoG Recordings

Aditya Narendra, Andy Bonnetto,  
Chayanon Kitkana, Paola Juárez,  
Ruman Ahmed Shaikh & Taima Crean



Afrovenator-Folk A: Nerdy Vampires



## > Venue: 2023 Neuromatch Academy Summer School on Computational Neuroscience

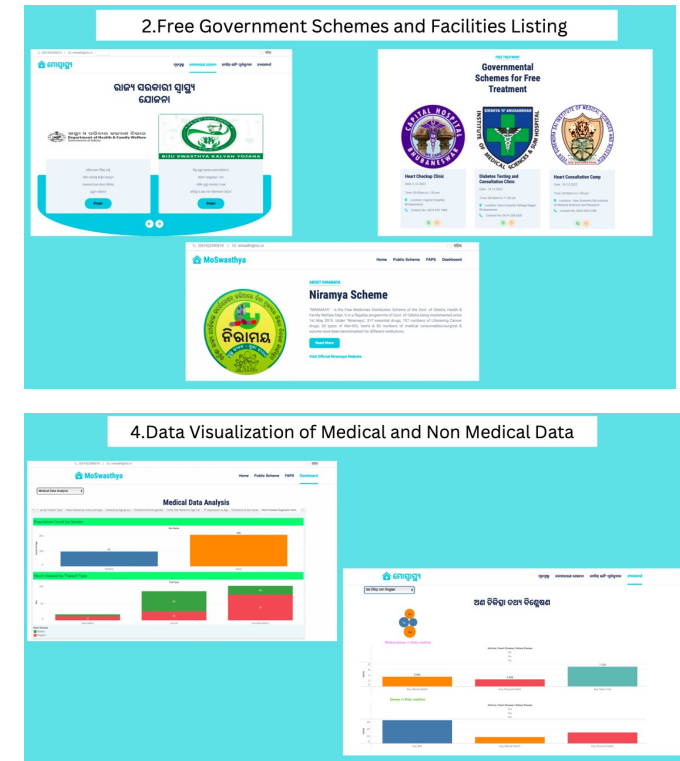
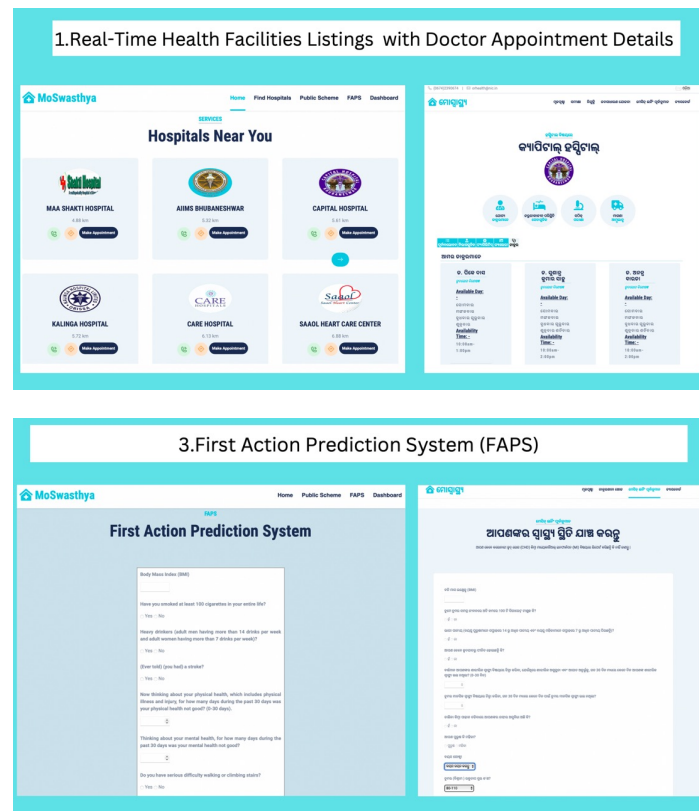
> **Overview:** This project focused on designing and evaluating a predictive framework for neural signal decoding in Brain-Computer Interface (BCI) systems using electrocorticography (ECoG) data. We investigated how temporal windowing, spatial feature selection, and dimensionality reduction influence the ability to forecast future motor states from cortical signals. By grouping channels based on Brodmann areas and applying PCA-driven feature compression, we identified anatomically relevant brain regions that consistently contributed to reliable prediction. We systematically analyzed the trade-offs between prediction horizon, model stability, and uncertainty, demonstrating that short-horizon forecasts achieve robust performance while longer horizons introduce rapid degradation. This work provided insights into the limits of linear predictive models for neural time-series data and highlighted key design considerations for building low-latency BCI systems.

> **Methods/Tools Used:** Python, Principal Component Analysis, Linear Regression

[\[Slides\]](#) || [\[Code\]](#)



Team: **COE-AI Pistons**  
Theme: **Healthcare**



> Venue: **Smart Odisha Hackathon 2022**

> **Overview:** MoSwasthya is a multi-lingual, healthcare accessibility, and risk-awareness platform developed as part of the *Smart Odisha Hackathon 2022* to address gaps in treatment-seeking behaviour for non-communicable diseases, with a focus on cardiovascular disorders. The system integrates real-time healthcare facility discovery, appointment booking, and government scheme awareness with a ML-based heart disease risk prediction module driven by non-medical user inputs. It also provides a health data visualization dashboard to promote long-term awareness and support future public health research. The platform was designed as a scalable, end-to-end digital health solution that reduces information asymmetry, improves early risk assessment, and enhances access to affordable and nearby clinical services.

> **Methods/Tools Used:** Python, HTML/CSS, Vision Transformers

> **Remarks:** This work won the 1<sup>st</sup> prize (\$2500) out of 1000 teams nationwide by the Government of Odisha.

[\[Slides\]](#) || [\[Code\]](#) || [\[Video\]](#)