Beyond the Surface: Advancing Skin Cancer Detection Across All Tones

STA 221 Fall 2024

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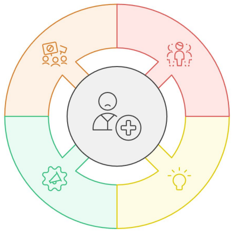
Introduction

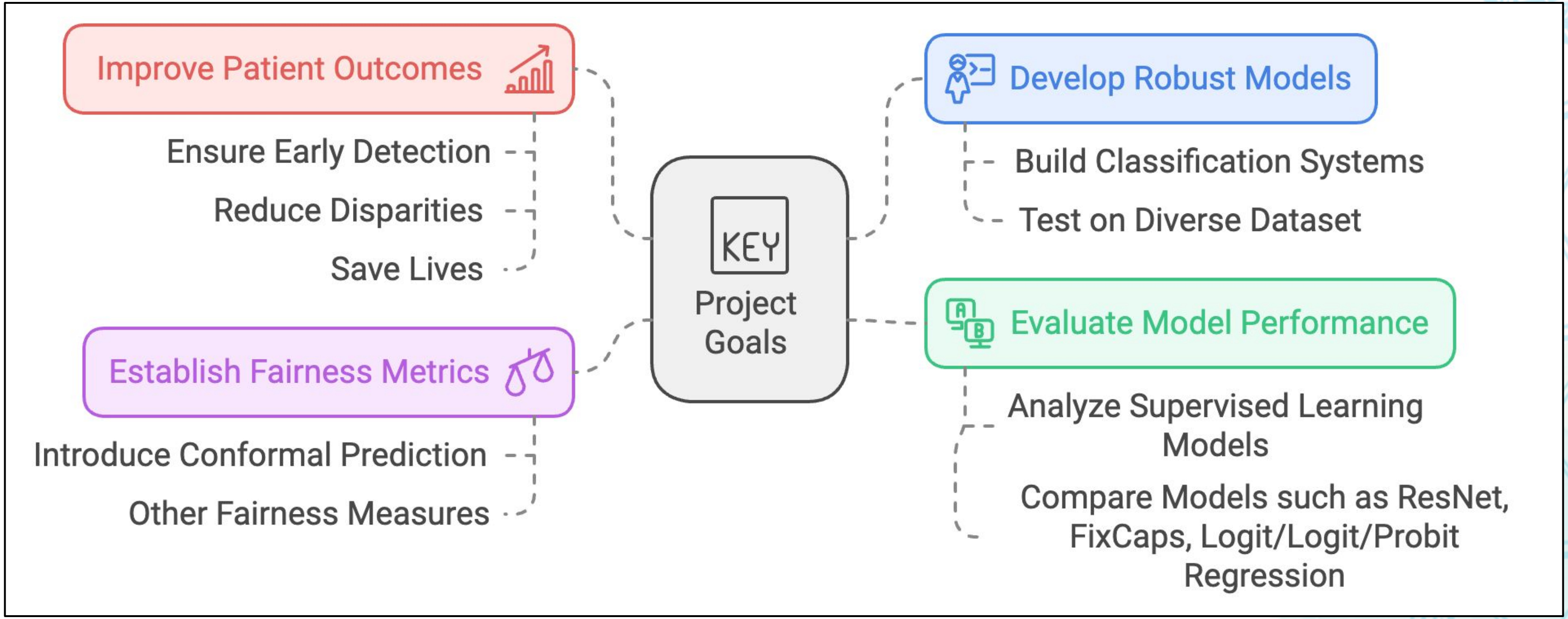
- **Revolutionizing Healthcare**
  - The intersection of AI and medicine is reshaping how we approach diagnostics and patient care.
- **Power of Image Classification**
  - Automated analysis of medical images accelerates diagnostic processes, improving efficiency and precision.
- **Impact on Skin Cancer Detection**
  - Early detection is critical for better outcomes, and AI-driven tools can make this process faster and more accurate.
- **Enhancing Decision-Making**
  - By integrating advanced technologies, healthcare providers can detect abnormalities and make informed decisions more effectively.

Motivation



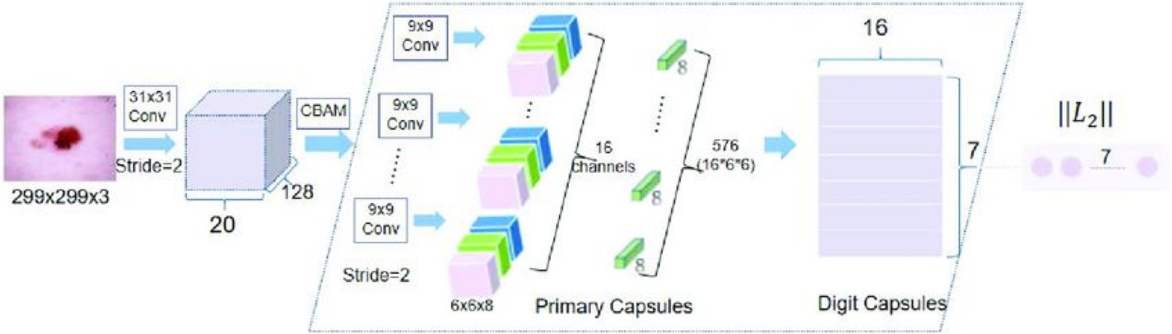
- **Highlighting Healthcare Disparities**
  - Current skin cancer detection models are biased toward lighter skin tones, leading to unequal diagnostic outcomes.
- **Raising Awareness**
  - Shine a spotlight on the ethical and scientific importance of inclusivity in medical AI tools.
- **Leveraging AI for Equity**
  - Show how technology can bridge gaps in healthcare access and quality across diverse populations.
- **Call to Action**
  - Inspire innovation in creating AI systems that prioritize fairness, inclusivity, and patient outcomes.

Goals of the Project



State of the Arts
- FixCaps: An Improved Capsules Network

- Advanced version of Capsule Networks (CapsNets) to capture spatial hierarchies in medical images for better generalization in medical imaging.
- Achieved improved accuracy i.e. 96.49% on HAM 10K dataset for skin lesion classification compared to conventional CNNs.
- Mitigates overfitting in smaller datasets like HAM10000, handles imbalanced and augmented data.

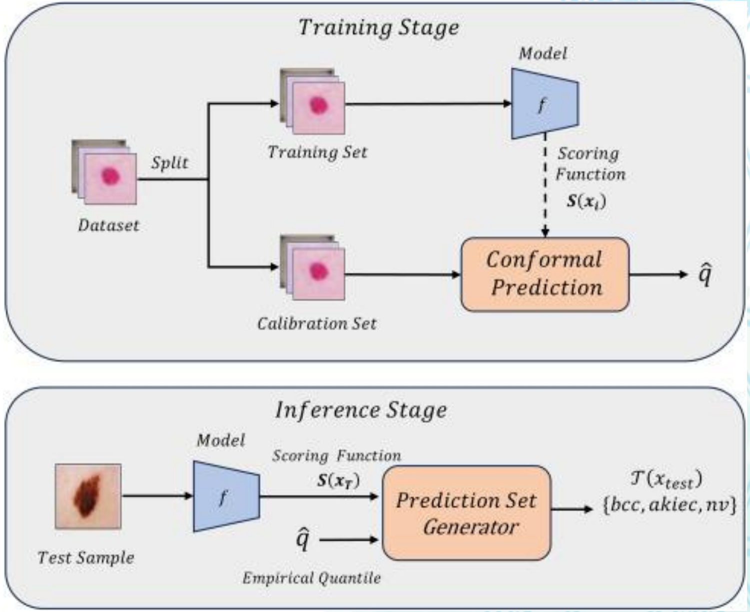


Literary Review - Fair Conformal Predictors for Applications in Medical Imaging

- To **evaluate** uncertainty quantification in medical imaging tasks.
- True label will be included in the **prediction set** with a probability of at least 1−α, achieving **marginal coverage**

$$P\Big(Y_{\text{test}} \in \mathcal{C}(X_{\text{test}})\Big) \geq 1 - \alpha.$$

- **Equal confidence levels** across dataset given calibration set is representative of the entire population.
- Can be extended to **Group-Balanced Conformal Prediction**



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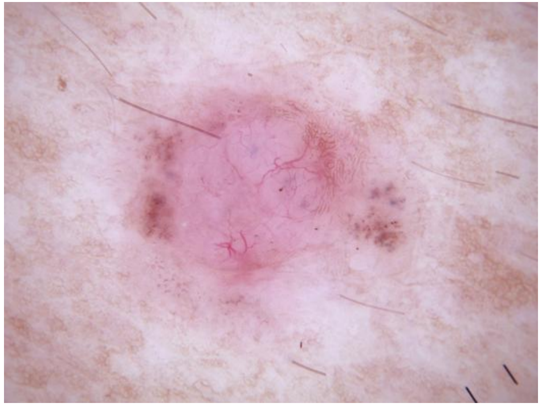
A demo of Prediction Set

Here is one test sample:

Prediction Set: C={'bcc', 'mel'}

True label: 'bcc'



True label included!

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Literary Review - Fair Conformal Predictors for Applications in Medical Imaging

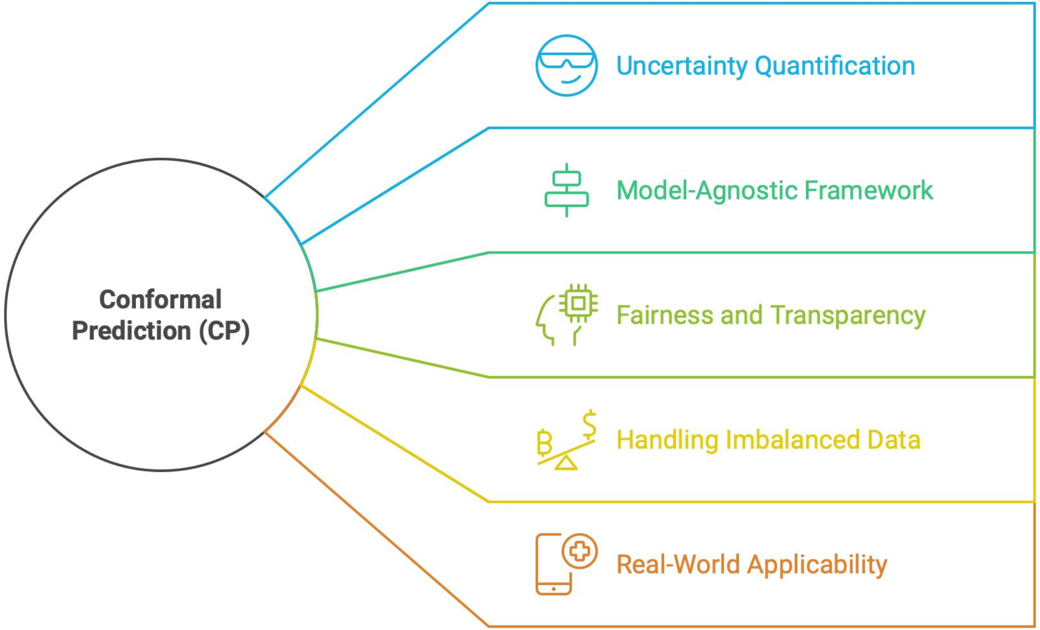
Training Set: Used to train a machine learning model.
.**Calibration Set**: Used to compute the empirical quantiles required for prediction set generation.
Scoring Function: This score reflects the likelihood or confidence of a prediction.
Conformal Prediction: Using the scores from the Calibration Set, CP computes the empirical quantile q^q^. This quantile is the threshold that determines which predictions will be included in the prediction set to achieve the desired confidence level.
Nonconformity Score Computation: "distance" between the true label and the predicted confidence.
Quantile Calculation:The 1−αquantile (e.g., 95th percentile for α=0.05α=0.05) of the nonconformity scores is computed. This quantile is the threshold (q^q^) for generating prediction sets that meet the desired confidence level.

2. Inference Stage

Prediction Set Generation:The score from the test sample is compared with the empirical quantile q^ from the calibration stage. Based on this comparison, a **Prediction Set** T(xtest) is generated. This set includes all possible classes (e.g., {bcc, akiec, nv}) that satisfy the required confidence level.

CP allows the user to specify confidence thresholds (e.g., 95%), enabling control over the trade-off between prediction set size and confidence.

Why Conformal Prediction



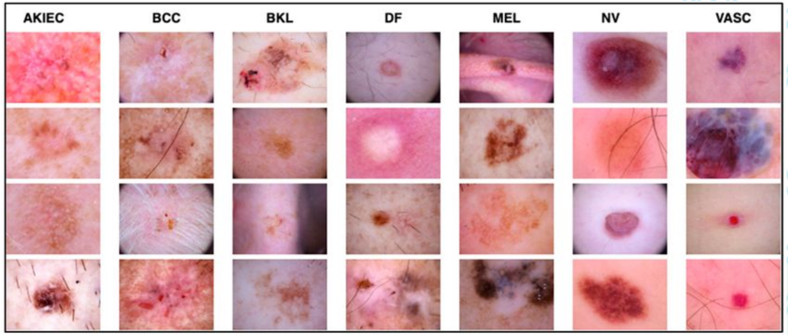
The **trick** is to —

construct a statistically valid **prediction set** based on the **softmax scores** of underlying models

Dataset

HAM10000 (Human Against Machine with 10000 training images**)**: Widely recognized dataset for medical image analysis.
https://www.kaggle.com/datasets/kmader/skin-cancer-mnist-ham10000
Size: 10,015 dermatoscopic images of skin lesions.
Key Features:

- `imageid`: Unique image identifier.
- `dx`: Diagnostic label (e.g., melanoma, nevus).
- `dxtype`: Diagnostic procedure type (e.g., histopathology).
- `age`, `sex`, `localization`: Patient and lesion details.
- `path`: Image file location.

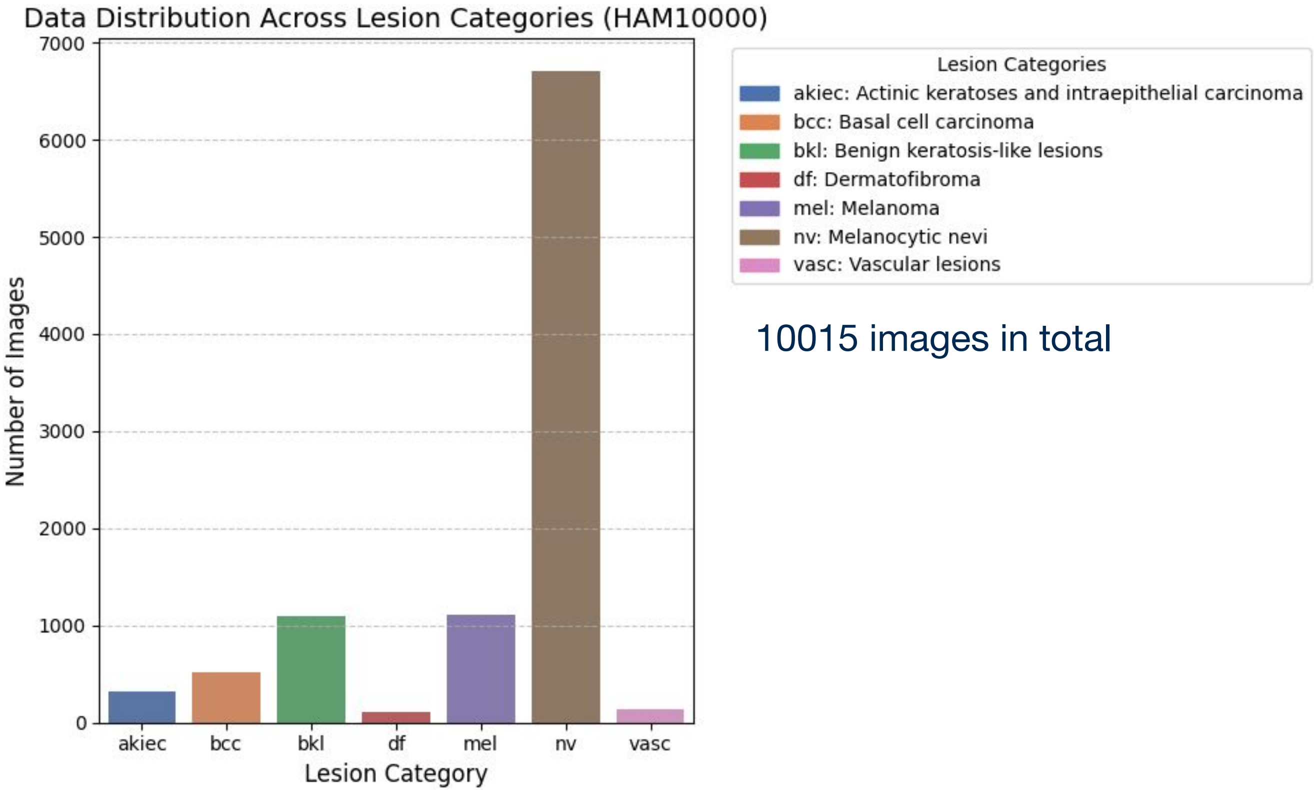


Lesion Categories:

- Melanocytic nevi, melanoma, keratosis-like lesions, basal cell carcinoma, actinic keratoses, vascular lesions, dermatofibroma.

Diversity: Includes images from various skin tones for fair analysis.

Dataset Distribution



10015 images in total

Dataset

Preprocessing:

- Resize, normalize, and augment images
- Encoded labels to numerical values
- Clean metadata for consistency

Test set: ISIC (International Skin Imaging Collaboration) dataset.

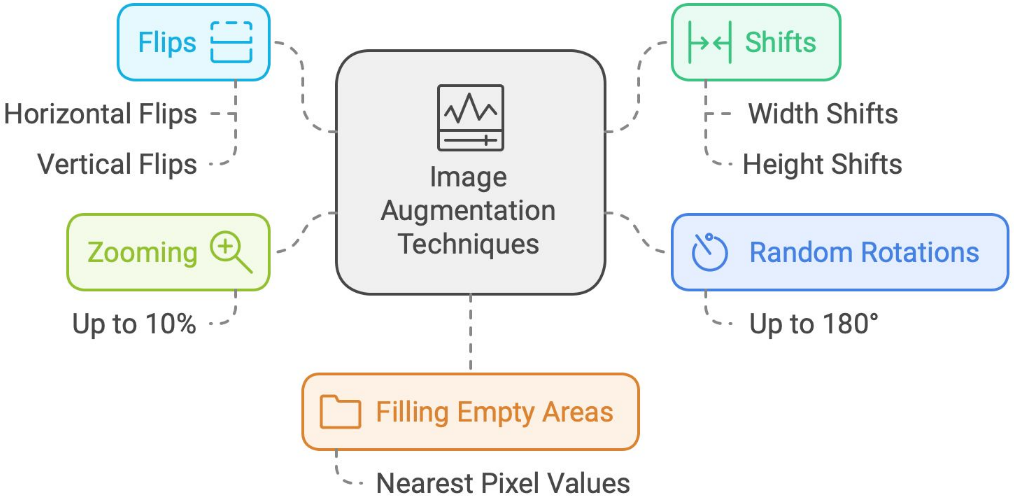
- Serves as a benchmark dataset for skin cancer classification challenges (~240 images)

Utilization:

- Images for training, lesion categories as target labels.

Significance: Diverse, well-categorized dataset ensures fairness and robustness in skin lesion classification.

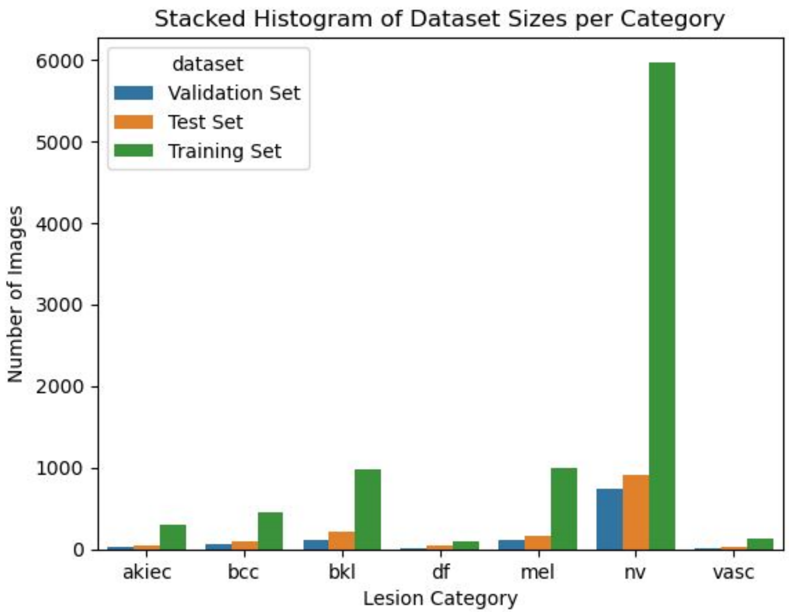
Dataset Augmentation

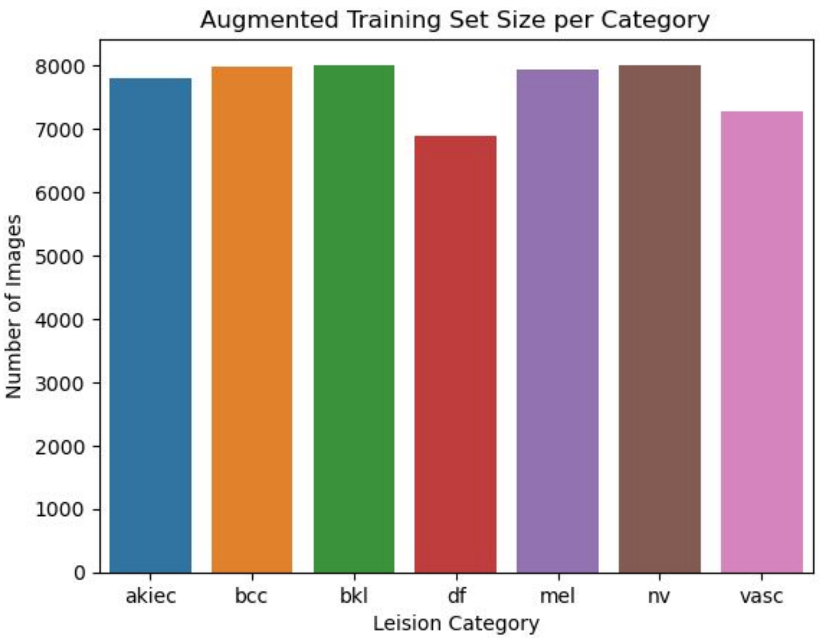


Final Dataset:

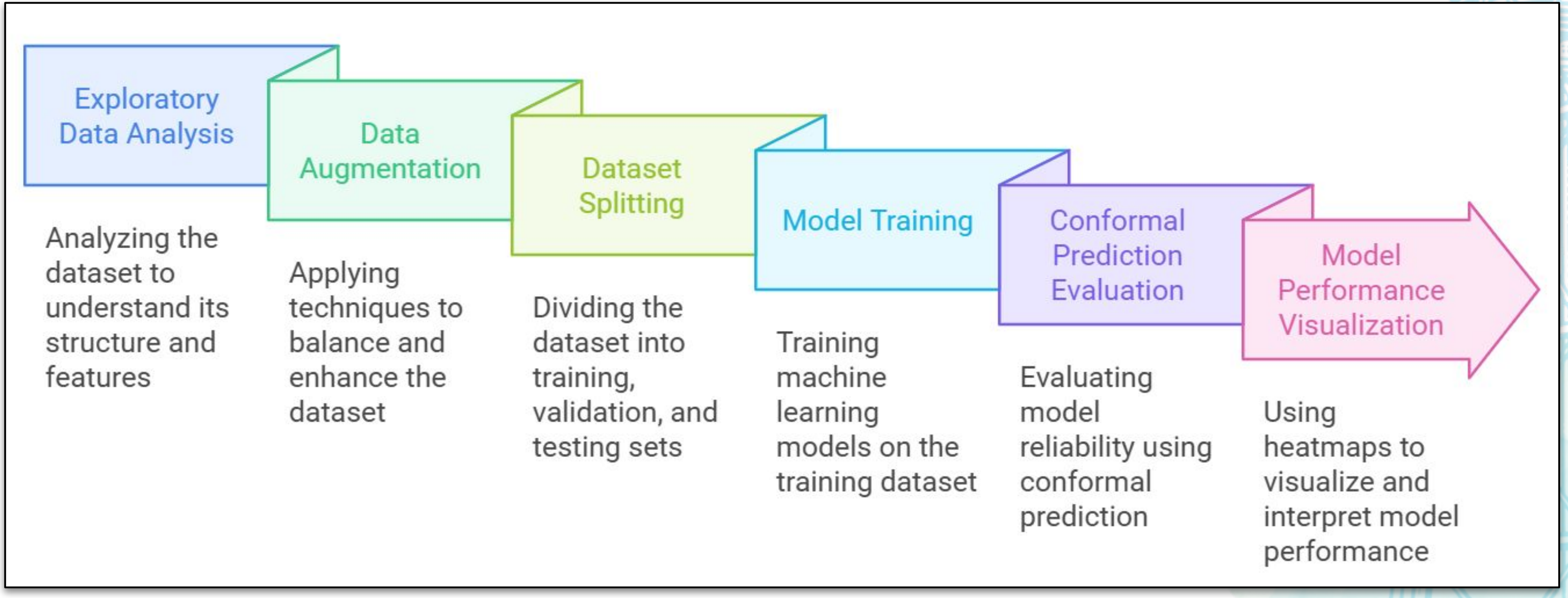
- 7 lesion categories, each with roughly 8000 images.
- Total dataset size: ~56,000 images.

Dataset Distribution





Methodology



Logit Regression

Logit Model: A regression model used for predicting the probability of a binary or categorical outcome. Uses the logistic function to model the relationship between the dependent variable and independent variables.

Why Logit for This Analysis?

Multinomial Logit:

- Extended to handle multi-class classification problems.
- Models probabilities for multiple classes using a softmax transformation.
- Provides probabilistic predictions for interpretability.

Challenges Faced:

- Computational complexity in high-dimensional data.
- High Dimensional Problem (p>>n): Panelization requires careful hyperparameter tuning via Cross Validation.

Logit Regression (on PC)

Preprocessing:

- Data standardized and encoded numerically for compatibility with the model.
- Principal Component Analysis (PCA) reduced dimensionality to 200 components.

Data Overview:

- Dataset includes resized 32×32 normalized images for feature extraction.

Optimization Techniques:

- **Hyperparameters:**
  - Regularization applied to the model to control overfitting.
  - PCA components optimized for balanced variance retention.
- **Solver:**
  - Logistic regression trained using the 'lbfgs' solver for faster convergence.

Logit Regression (from PC to GPU Cluster)

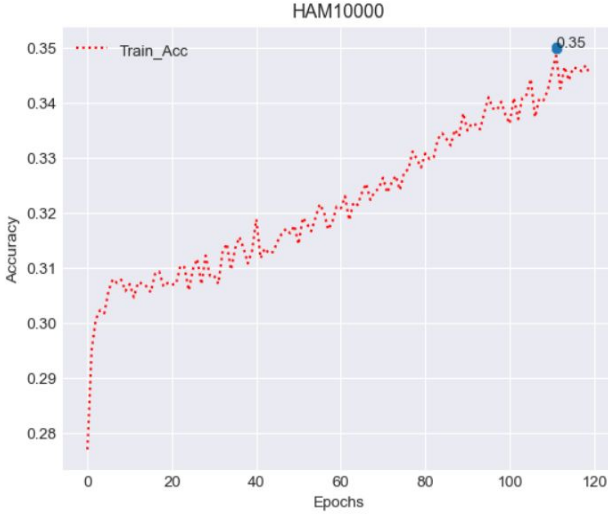
Drive:

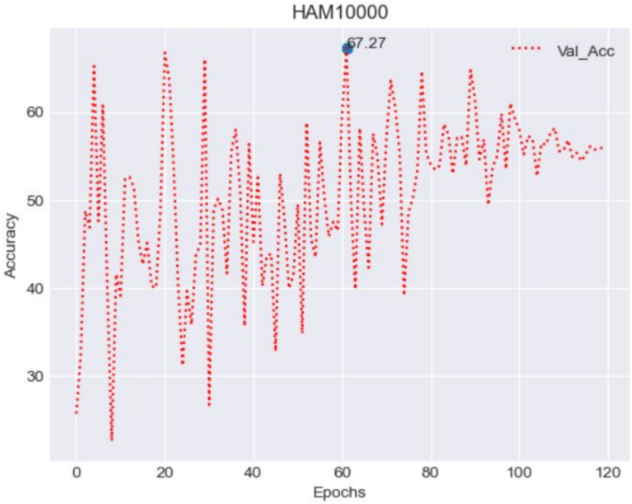
- **Calculation Efficiency:**
  - Roughly 4 hours/epoch on PC.
  - Roughly 1min/epoch on GPU Cluster (1 10GB slice from NVIDIA Ampere A100-80gb GPUs).
- **Multinomial Logit: Single Softmax Layer After Image Flattening**
  - More advanced Deep Learning Models usually use a softmax layer as its last layer.
  - Logit Regression is a good base model to start with.

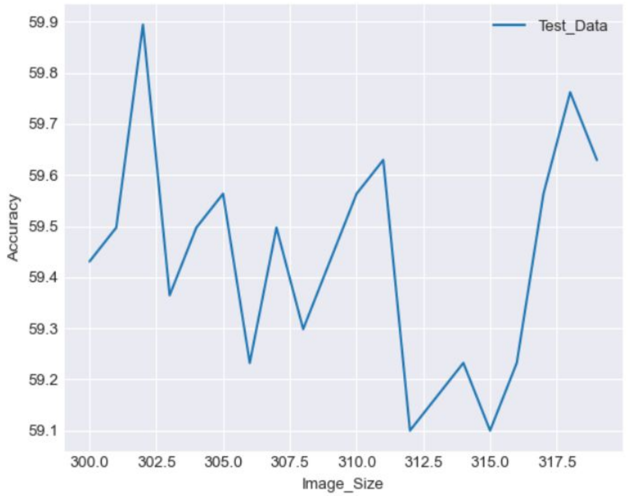
Model	Params(M)	FLOPs(G)	FPS
LogitRegression	1.88	0.0	13797.05

Logit Regression (on GPU Cluster)

Best train accuracy: 35%
Best validation accuracy: 67.27%
Best test accuracy: 59.9%

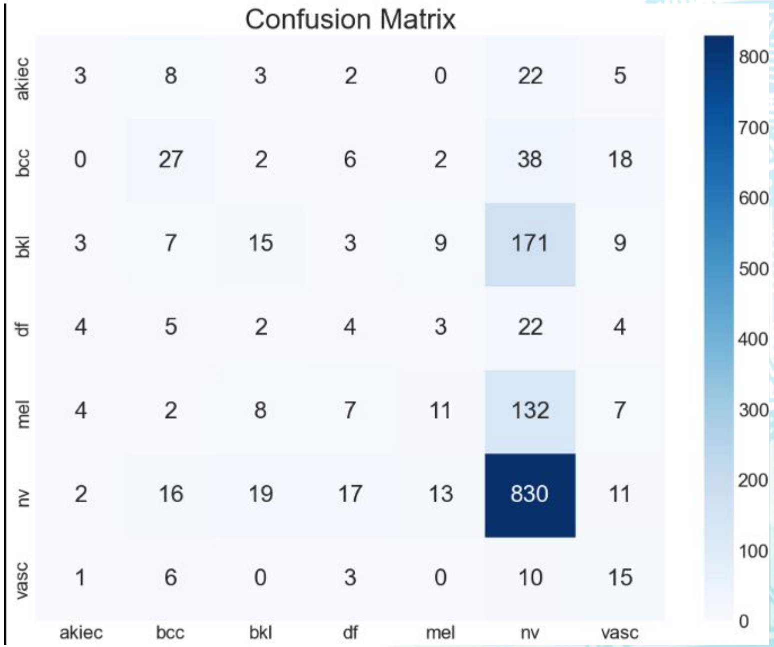






Logit Regression Test Result (on GPU Cluster)

Type	Precision	Recall	F1	Accuracy
akiec	0.1765	0.07	0.1	
bcc	0.3803	0.29	0.329	
bkl	0.3061	0.069	0.113	
df	0.0952	0.091	0.093	
mel	0.2895	0.064	0.105	
nv	0.6776	0.914	0.778	
vasc	0.2174	0.429	0.288	
Total:				0.5989



Inception V3 model

Inception V3 Model: A deep convolutional neural network (CNN) architecture designed for image classification and feature extraction tasks.

Why Inception V3 for This Analysis?

Key Features:

- A Deep Learning model with relatively few parameters (compared to VGG) and DL training techniques (Batch Normalization, Auxiliary classifier,...)
  - ✓ Easy and Stable to train
- Relies on "Inception Modules": blocks designed to capture features at multiple scales
  - ✓ Capture both Fine-Grained and Coarse Features of Images

Model	Params(M)	FLOPs(G)	FPS
InceptionV3	21.8	5.75	142.97

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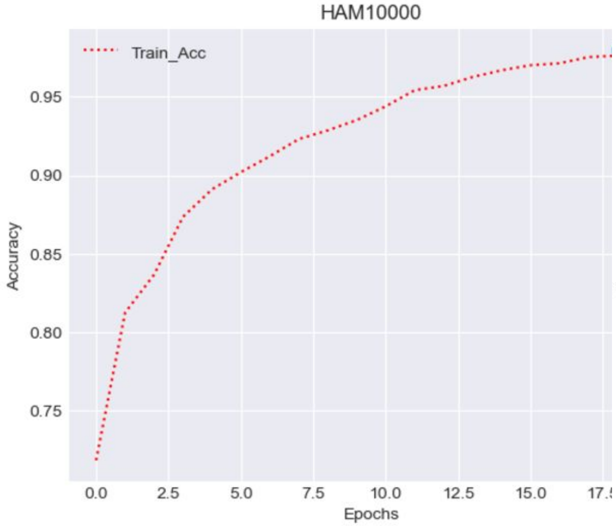
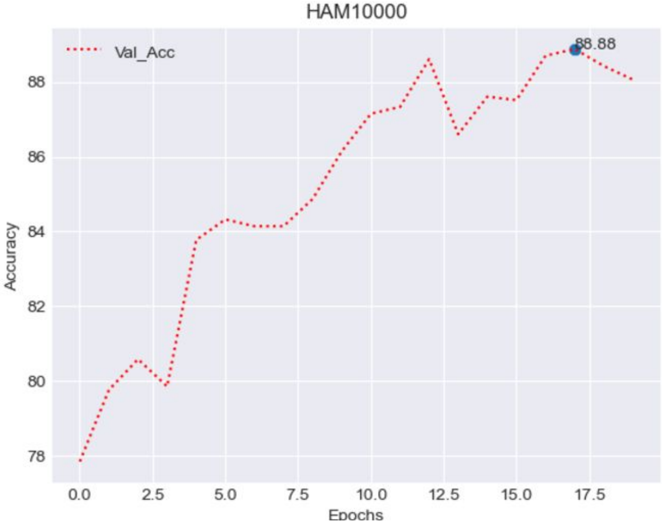
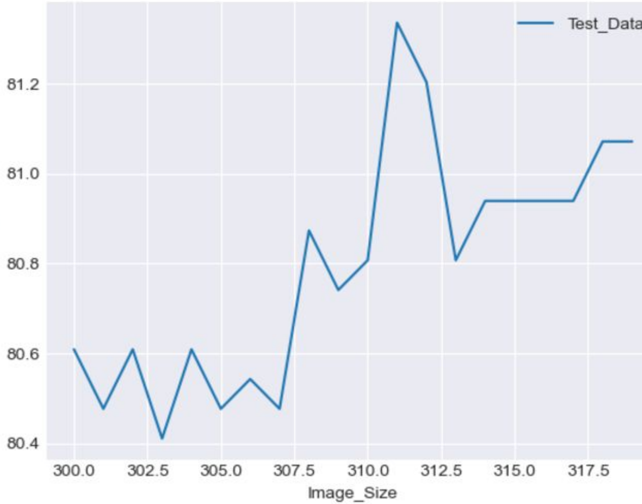
Results

Best train accuracy: 98%
Best validation accuracy: 88.88%
Best test accuracy:81.34%







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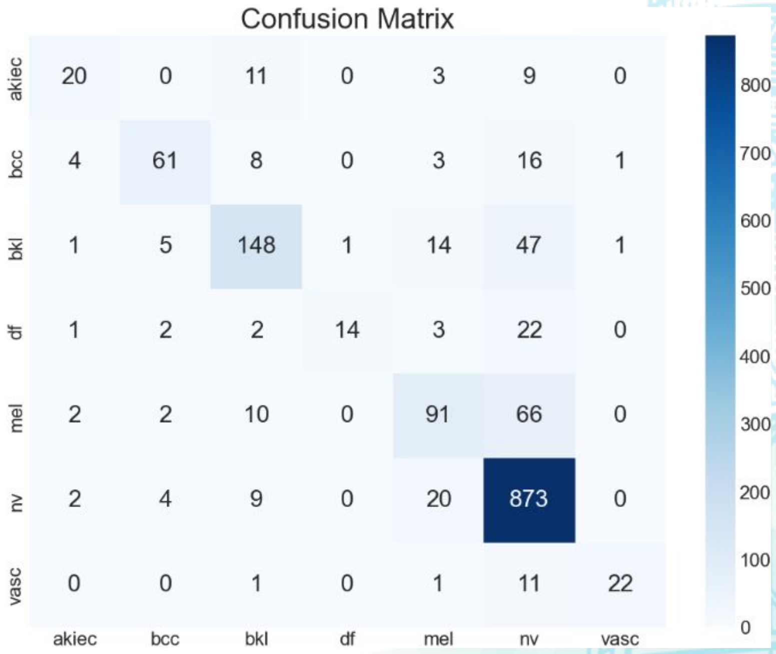
Test Result

Type	Precision	Recall	F1	Accuracy
akiec	0.6667	0.465	0.548	
bcc	0.8243	0.656	0.731	
bkl	0.7831	0.682	0.729	
df	0.9333	0.318	0.475	
mel	0.6741	0.532	0.595	
nv	0.8362	0.961	0.894	
vasc	0.9167	0.629	0.746	
Total:				0.8134



Model Comparison - Conformal Prediction

Marginal Coverage

$$P\Big(Y_{\text{test}} \in \mathcal{C}(X_{\text{test}})\Big) \geq 1 - \alpha.$$

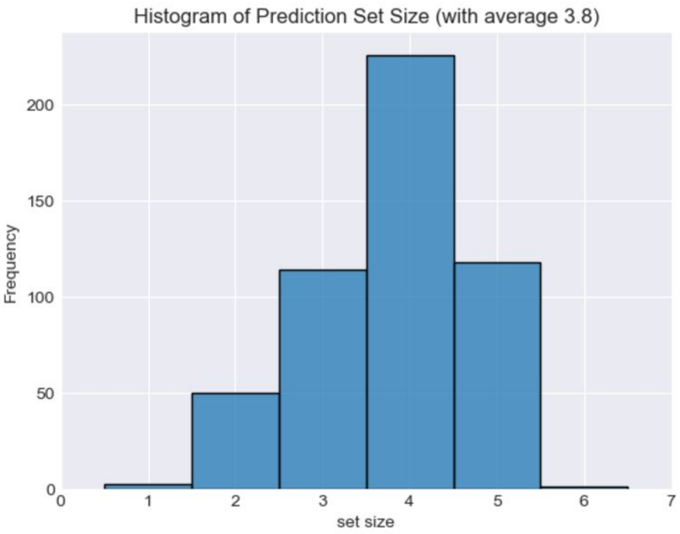
Rangularized Adaptive Prediction Sets (RAPS) on Validation Set:

Experiment Result:

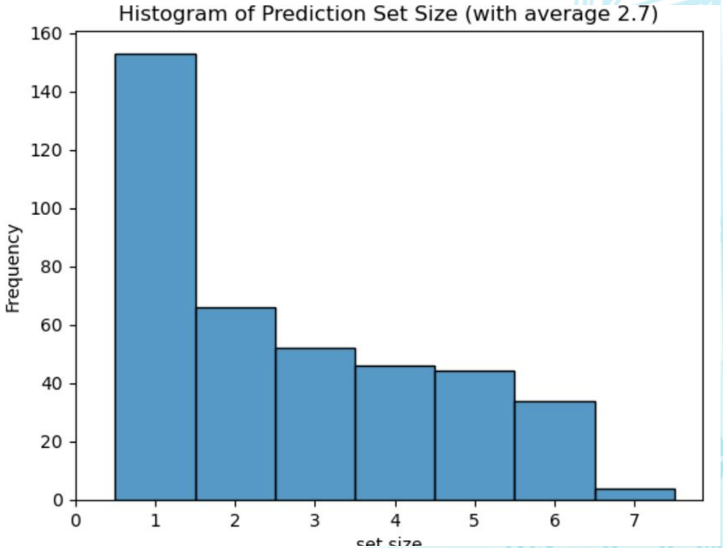
Sig. Level alpha=0.1

n=1000 for Calibration

n=511 for Validation



RAPS Size Distribution for Logit Regression



RAPS Size Distribution for Inception V3

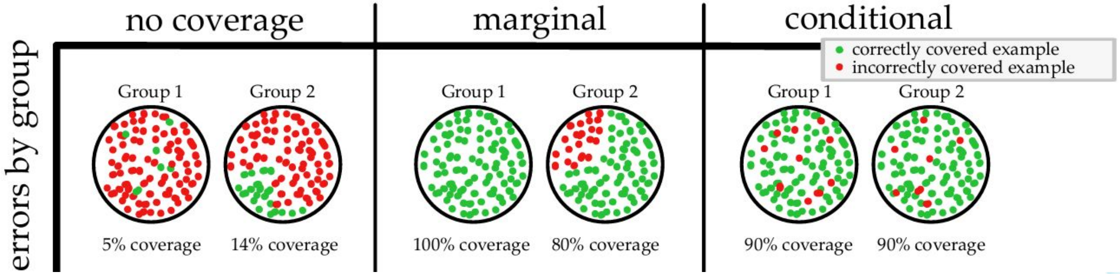
Model Comparison
- Conformal Prediction

Marginal Coverage

$$P\Big(Y_{\text{test}} \in \mathcal{C}(X_{\text{test}})\Big) \geq 1 - \alpha.$$

Adaptability Evaluation:

- **Marginal Coverage** is not adequate for **Conditional Coverage** $\mathbb{P}\left[Y_{\text{test}} \in \mathcal{C}(X_{\text{test}}) \mid X_{\text{test}}\right] \geq 1 - \alpha.$



- Marginal Coverage is not adequate for Conditional Coverage:
  - ✓ Introduce SSC metric: (SSC closer to 1-alpha the better)

$$\min_{g \in \{1,\dots,G\}} \frac{1}{|\mathcal{I}_g|} \sum_{i \in \mathcal{I}_g} \mathbb{1}\left\{Y_i^{(\text{val})} \in \mathcal{C}\left(X_i^{(\text{val})}\right)\right\}$$

Experiment Result:

Sig. Level alpha=0.1, 1-alpha=0.9

SSC for Logit Regression: 0.5

SSC for Inception V3: 0.83

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Model Comparison
- Conformal Prediction

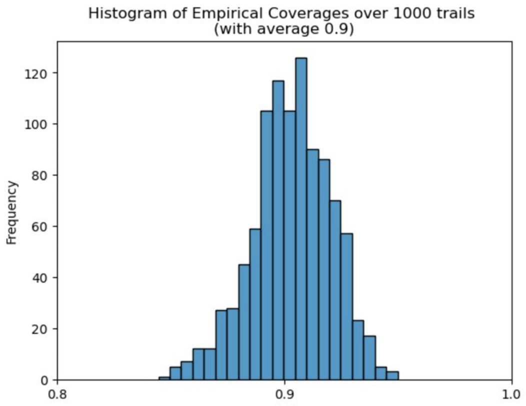
Correctness Check: running CP over R trials with new calibration and validation sets, and then calculating the empirical coverage Cj for each: (Average of Cj should center around 1-alpha)

$$C_j = \frac{1}{n_{\mathrm{val}}} \sum_{i=1}^{n_{\mathrm{val}}} \mathbb{1}\left\{Y_{i,j}^{(\mathrm{val})} \in \mathcal{C}_j\left(X_{i,j}^{(\mathrm{val})}\right)\right\}, \text{ for } j = 1, \ldots, R$$

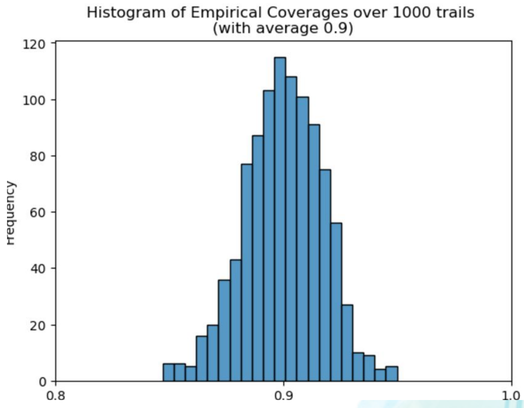
Experiment Result:

Sig. Level alpha=0.1

Ran 1000 trails for Logit Regression and Inception V3



Empirical Coverage for Logit Regression



Empirical Coverage for Inception V3

Next Steps and Conclusions

- **Next Steps:**
  - ➢ Resnet : We will train the model from scratch and apply CP to observe results
  - ➢ Fixcaps: the best model known for HAM10K, we will use the network framework and then apply CP
  - ➢ Comparing all these 4 models
- **Conclusions:**
  - ➢ Through this project we successfully implemented and evaluated models using Logit regression and Inception V3, demonstrating initial progress in skin cancer classification.
  - ➢ We hope this project lays a foundation for inclusive, equitable AI in skin cancer detection, bridging gaps in healthcare diagnostics.

References

[1] M. Li, H. Chen, J. Peng, X. Li, Y. Zhang, and J. Lin, *FixCaps: An Improved Capsules Network for Diagnosis of Skin Cancer*, Proceedings of the AAAI Conference on Artificial Intelligence, vol. 36, no. 11, pp. 12165-12173,2022. Available: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9791221

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[4] Angelopoulos, A. N., Bates, S., A Gentle Introduction to Conformal Prediction and Distribution-Free Uncertainty Quantification, arXiv:2107.07511, 2021. Available: https://arxiv.org/abs/2107.07511

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