Professional Certificate in AI for Digital Pathology

Validation and Interpretation of AI Results

Artificial Intelligence (AI): The simulation of human intelligence processes by machines, especially computer systems. These processes include learning (the acquisition of information and rules for using the information), reasoning (using the rules to reach approximate or definite conclusions), and self-correction.

Digital Pathology: The practice of pathology with the use of digital images of surgical pathology slides, created by whole slide imaging (WSI) scanners. This practice can be used for various purposes, such as education, research, and primary diagnosis.

Validation: The process of evaluating an AI model to ensure it is accurate, reliable, and safe for use. Validation involves testing the model on a separate dataset not used during training, and comparing the results to a set of predefined performance metrics.

Interpretation: The process of understanding and explaining the results generated by an AI model. Interpretation involves identifying patterns and trends in the data, and communicating the findings in a clear and concise manner to stakeholders.

Whole Slide Imaging (WSI): A technology used to create digital images of glass slides in pathology. WSI scanners capture high-resolution images of the entire slide, allowing for digital analysis and interpretation.

Training dataset: A set of data used to train an AI model. The model learns from this data by identifying patterns and relationships between input variables and output variables.

Test dataset: A set of data used to evaluate the performance of an AI model. The model is tested on this data to ensure it can accurately predict outcomes on new, unseen data.

Performance metrics: Quantitative measures used to evaluate the performance of an AI model. Examples include accuracy, precision, recall, and F1 score.

Ground truth: The true value or outcome of a sample in a dataset. Ground truth is used as a reference standard to evaluate the performance of an AI model.

Overfitting: A common issue in AI model training where the model learns the training data too well, resulting in poor performance on new, unseen data. Overfitting occurs when the model is too complex and captures the noise in the training data.

Underfitting: A common issue in AI model training where the model does not learn the training data well enough, resulting in poor performance on both the training data and new, unseen data. Underfitting occurs when the model is not complex enough to capture the patterns and relationships in the data.

Feature engineering: The process of selecting and transforming variables (features) in a dataset to improve the performance of an AI model. Feature engineering can include techniques such as scaling, normalization,

and dimensionality reduction.

Bias: A systematic tendency in an AI model to produce results that are consistently higher or lower than the true value. Bias can occur due to issues in the data, such as selection bias or measurement bias.

Variance: The amount by which an AI model's predictions vary for different subsets of the training data. High variance can result in poor performance on new, unseen data.

Cross-validation: A technique used to evaluate the performance of an AI model by splitting the dataset into multiple subsets, and training and testing the model on each subset. Cross-validation helps to reduce bias and variance in the model's performance.

Confusion matrix: A table used to evaluate the performance of an AI model. The matrix shows the number of true positive, true negative, false positive, and false negative predictions made by the model.

Precision: A performance metric that measures the proportion of true positive predictions out of all positive predictions made by an AI model. Precision is calculated as true positives / (true positives + false positives).

Recall: A performance metric that measures the proportion of true positive predictions out of all actual positive samples in the data. Recall is calculated as true positives / (true positives + false negatives).

F1 score: A performance metric that is the harmonic mean of precision and recall. The F1 score is a balanced metric that takes into account both false positives and false negatives.

ROC curve: A graphical representation of the performance of an AI model at different classification thresholds. The ROC curve shows the trade-off between the true positive rate and the false positive rate.

AUC: The area under the ROC curve. AUC is a performance metric that measures the overall performance of an AI model across all classification thresholds.

Explainability: The ability of an AI model to provide clear and understandable explanations for its decisions and predictions. Explainability is important in high-stakes applications, such as healthcare, where stakeholders need to understand and trust the model's decisions.

Feature importance: A technique used to identify the most important features in a dataset for an AI model's predictions. Feature importance can help to identify which variables are driving the model's decisions.

Partial dependence plots: A technique used to visualize the relationship between a specific feature and the output of an AI model. Partial dependence plots can help to identify non-linear relationships and interactions between features.

SHAP values: A technique used to explain the output of an AI model by quantifying the importance of each feature for a specific prediction. SHAP values can help to identify which features are driving the model's decisions.

Model transparency: The degree to which an AI model's internal workings and decision-making processes are understandable and interpretable. Model transparency is important for building trust and confidence in

the model's decisions.

Ethics: A set of moral principles that govern the use of AI in healthcare. Ethical considerations include issues such as privacy, fairness, and accountability.

Privacy: The protection of personal health information (PHI) in digital pathology. Privacy concerns include issues such as data breaches, unauthorized access, and data sharing.

Fairness: The assurance that AI models do not discriminate against certain groups of patients based on factors such as race, gender, or age. Fairness is important to ensure that all patients receive equitable care.

Accountability: The responsibility for the decisions and outcomes of AI models in digital pathology. Accountability includes issues such as transparency, explainability, and liability.

Regulations: The legal framework that governs the use of AI in healthcare. Regulations include issues such as data privacy, model transparency, and patient safety.

Quality control: The process of ensuring that AI models in digital pathology meet certain standards of quality and performance. Quality control includes issues such as validation, testing, and maintenance.

Data governance: The management of data in digital pathology, including issues such as data security, privacy, and quality. Data governance is important to ensure that data is accurate, reliable, and trustworthy.

Data lineage: The history and origin of data in digital pathology. Data lineage is important to ensure that data is trustworthy and can be traced back to its source.

Data curation: The process of selecting, cleaning, and transforming data in digital pathology. Data curation is important to ensure that data is accurate, reliable, and relevant for AI model training.

Data preprocessing: The process of preparing data for AI model training in digital pathology. Data preprocessing includes steps such as normalization, scaling, and feature engineering.

Data augmentation: A technique used to increase the size and diversity of a training dataset in digital pathology. Data augmentation involves creating new synthetic samples by applying transformations such as rotation, flipping, and cropping to the existing data.

Transfer learning: A technique used to leverage pre-trained AI models for new tasks in digital pathology. Transfer learning involves fine-tuning a pre-trained model on a new dataset to adapt it to a specific task.

Ensemble learning: A technique used to combine multiple AI models to improve performance in digital pathology. Ensemble learning can help to reduce bias and variance in the model's performance.

Active learning: A technique used to select the most informative samples for AI model training in digital pathology. Active learning involves selecting samples that are uncertain or difficult for the model to classify, and requesting their labels from a human expert.

Online learning: A technique used to train AI models in real-time as new data becomes available in digital