1. **Problem Definition & Clinical Criteria**

* **Objective**: Classify CTA scans as "diagnostic" (suitable for clinical diagnosis) or "non-diagnostic" (compromised by artifacts/noise).
* **Key Quality Metrics** (defined by radiologists):
  + **Motion Artifacts**: Blurring from patient movement.
  + **Contrast Opacification**: Adequate vessel enhancement (e.g., HU > 250 in arteries).
  + **Signal-to-Noise Ratio (SNR)**: Sufficient image clarity.
  + **Coverage**: Complete anatomical coverage (e.g., aorta to iliac arteries).
  + **Reconstruction Parameters**: Correct slice thickness/kernel.

2. **Data Collection & Annotation**

* **Dataset Sourcing**:
  + 5,000+ CTA scans from diverse sources (hospitals, public datasets like [DeepLesion](https://nihcc.app.box.com/v/DeepLesion)).
  + Ensure variability: scanners (Siemens, GE), protocols, and pathologies.
* **Annotation**:
  + **Radiologist Labeling**: 3+ experts label each scan as diagnostic/non-diagnostic (with reasons).
  + **Inter-rater Agreement**: Use Fleiss' κ to resolve discrepancies.
  + **Metadata**: Include DICOM headers (kVp, contrast timing, slice thickness).

3. **Preprocessing Pipeline**

* **DICOM Handling**: Extract pixel arrays and metadata using pydicom.
* **Windowing**: Focus on vascular structures (e.g., WW/WL: 700/100 HU).
* **Normalization**: Scale pixel values to [0, 1] using z = (x - min)/(max - min).
* **Resampling**: Standardize slice thickness (e.g., 1mm³ isotropic) via B-spline interpolation (SimpleITK).
* **Volume of Interest (VOI)**: Crop to relevant anatomy (e.g., heart for coronary CTA) using U-Net-based segmentation.

4. **Model Architecture**

* **Backbone Choice**: **3D ResNet-50** or **EfficientNet3D** for spatial-volume feature extraction.
* **Key Adaptations**:
  + Input: 3D volumes (e.g., 128×128×128 voxels).
  + Channel Handling: Process single-channel (grayscale) data.
  + Transfer Learning: Initialize weights from models pretrained on [RadImageNet](https://radimagenet.com/).
* **Output Layer**: Sigmoid activation for binary classification.

5. **Training Strategy**

* **Loss Function**: **Weighted Binary Cross-Entropy** to handle imbalance (e.g., 20% non-diagnostic).
* **Optimizer**: AdamW (lr=1e-4, weight decay=1e-5).
* **Augmentation** (3D-specific):
  + Spatial: Random rotation (±15°), flips, elastic deformations.
  + Intensity: Gaussian noise, contrast adjustments.
  + **MONAI Transforms**: Rand3DElastic, RandAdjustContrast.
* **Regularization**: Dropout (0.3), early stopping (patience=10 epochs).

6. **Explainability & Clinical Trust**

* **Grad-CAM**: Highlight regions influencing decisions (e.g., motion artifacts in coronary arteries).
* **SHAP Values**: Quantify feature importance (e.g., contrast HU, noise levels).

7. **Evaluation Metrics**

* **Primary**: AUC-ROC, F1-score (due to class imbalance).
* **Secondary**: Sensitivity (recall) > 95% to minimize false negatives (critical for non-diagnostic misses).
* **Confusion Matrix Analysis**: Focus on reducing Type II errors.

8. **Deployment & Integration**

* **Inference Engine**: FastAPI backend with ONNX runtime for <5s/scan prediction.
* **DICOM Integration**:
  + Input: Receive scans via DICOMweb from PACS.
  + Output: Push results as DICOM-SR structured reports.
* **Fallback Mechanism**: Low-confidence predictions flagged for radiologist review.

9. **Validation & Compliance**

* **Testing**:
  + **Holdout Set**: 20% of data for final evaluation.
  + **External Validation**: Test on unseen datasets (e.g., from different hospitals).
* **Regulatory**: Adhere to FDA/CE guidelines (ISO 13485), MDR compliance.

Tools & Libraries

* **Data Processing**: PyDICOM, SimpleITK, MONAI.
* **Modeling**: PyTorch Lightning, MONAI (3D CNNs), scikit-learn (metrics).
* **Explainability**: Captum (Grad-CAM), SHAP.
* **Deployment**: FastAPI, Orthanc (DICOM server), NVIDIA Triton (GPU inference).

Challenges & Mitigations

* **Data Scarcity**: Use generative models (e.g., StyleGAN3D) for synthetic non-diagnostic scans.
* **Artifact Variability**: Train with adversarial examples (e.g., simulated motion artifacts via Gaussian blurring).
* **Clinical Adoption**: Co-develop with radiologists; integrate into workflow tools (e.g., PACS viewers).