ECG AI Diagnosis Report Structure (15 Pages)

Page Distribution Overview

- **Cover Page**: 1 page
- **Main Content**: 12-13 pages
- **References**: 1-2 pages

Detailed Section Structure

1. Cover Page (1 page)

- University header and course information
- Report title: "AI-Based ECG Diagnosis System for Cardiovascular Disease Detection"
- Team member names and student IDs
- Date of submission
- Declaration of Originality (included in LaTeX template)

2. Abstract (0.5 pages)

- **Content**: 150-200 words
- Problem statement and significance
- Brief methodology overview
- Key findings and model performance
- Clinical implications

3. Introduction (1.5-2 pages)

Following the "Further Instruction" framework:

- **Problem Context** (0.5 pages):
    - CVD statistics and AFIB significance
    - ECG interpretation challenges in clinical settings
    - Need for AI-assisted diagnosis

- **Scope and Specifications** (0.5 pages):
    - Target conditions: NORM, AFIB, AFLT, 1dAVb, RBBB, LBBB
    - System requirements: accuracy, transparency, confidence flagging
    - Clinical deployment context
- **Objectives and Contributions** (0.5 pages):
    - Research objectives
    - Expected contributions to clinical practice

4. Literature Review (3-3.5 pages)

Structured survey with purpose-driven analysis:

- **ECG Foundation Models Evolution** (1 page):
    - From traditional CNNs to foundation models
    - Self-supervised learning in ECG analysis
    - Transfer learning advantages for medical data
- **Target Foundation Models** (1.2 pages):
    - **HuBERT ECG Model**:
        - Architecture based on speech processing HuBERT
        - Self-supervised pre-training on large ECG datasets
        - Multi-lead ECG representation learning
        - Performance on arrhythmia detection tasks
    - **ECG Founder Model**:
        - Foundation model design principles
        - Pre-training strategies and datasets
        - Fine-tuning capabilities for specific conditions
        - Reported benchmark performances
- **Explainable AI in ECG Analysis** (0.5 pages):
    - Feature-based interpretation methods

    - Clinical feature extraction importance
    - Integration of domain knowledge with AI models
- **Selection Justification** (0.3-0.5 pages):
    - Why these two foundation models were selected
    - Comparison criteria: performance, interpretability, clinical relevance

5. Benchmarking Results (2.5-3 pages)

Head-to-head foundation model comparison:

- **Benchmark Datasets** (0.5 pages):
    - **MIMIC-IV ECG Dataset**:
        - Dataset characteristics (size, demographics, conditions)
        - Clinical relevance and quality annotations
        - Preprocessing and data split strategies
    - **PhysioNet Challenge 2021 Dataset**:
        - Competition context and evaluation metrics
        - Dataset diversity and representativeness
        - Alignment with target conditions (AFIB, AFLT, etc.)
- **Quantitative Performance Analysis** (1.5 pages):
    - **Comprehensive Metrics Table**:
        - Per-condition performance (NORM, AFIB, AFLT, 1dAVb, RBBB, LBBB)
        - F1-Score, AUC-ROC, Accuracy, Sensitivity, Specificity
        - Macro and micro-averaged metrics
        - Statistical significance testing (p-values, confidence intervals)
    - **Cross-Dataset Generalization**:
        - MIMIC-IV → PhysioNet 2021 transfer performance

        - PhysioNet 2021 → MIMIC-IV transfer performance
        - Robustness analysis across different patient populations
    - **Computational Efficiency Comparison**:
        - Training time, inference speed, memory requirements
- **Qualitative Analysis** (0.5-1 pages):
    - **Model Interpretability Assessment**:
        - Foundation model feature representation quality
        - Attention pattern analysis (if applicable)
        - Clinical relevance of learned representations
    - **Failure Case Analysis**:
        - Challenging samples where models disagree
        - Common misclassification patterns
        - Clinical significance of errors

6. Methodology (3-3.5 pages)

Your hybrid AI solution development:

- **Foundation Model Selection and Adaptation** (1 page):
    - **Model Selection Rationale**:
        - Benchmarking results analysis
        - Selection of best-performing foundation model
        - Justification based on clinical requirements
    - **Model Fine-tuning Strategy**:
        - Target condition-specific adaptation
        - Transfer learning from general ECG representations
        - Hyperparameter optimization approach
- **NeuroKit-Based Explainability Framework** (1.2 pages):
    - **ECG Feature Extraction Pipeline**:

        - NeuroKit2 implementation details
        - Clinical feature categories (P-wave, QRS, T-wave characteristics)
        - Heart rate variability metrics
        - Morphological and temporal features
    - **Feature Visualization System**:
        - Automated ECG feature plotting
        - Clinical annotation generation
        - Interactive visualization components
    - **Integration Architecture**:
        - Feature extraction → Visualization → API workflow
        - Data preprocessing and normalization steps
- **ChatGPT 4.1 Integration for Clinical Reporting** (0.8 pages):
    - **API Integration Framework**:
        - Feature data formatting for LLM input
        - Prompt engineering for clinical interpretation
        - Response parsing and validation
    - **Clinical Report Generation**:
        - Template-based reporting structure
        - Integration of quantitative features with qualitative insights
        - Medical terminology and clinical reasoning
    - **Quality Assurance**:
        - Output validation mechanisms
        - Clinical consistency checks
- **Test Results on Provided Dataset** (0.5-1 pages):
    - **Diagnostic Performance**:

        - Selected model performance on validation set
        - Per-condition accuracy metrics
        - Confidence threshold optimization
    - **Explainability Demonstration**:
        - Sample ECG feature extraction results
        - Generated clinical reports examples
        - Clinician feedback on report quality (if available)

7. AI Ethics (1-1.5 pages)

Alignment with Australia's AI Ethics Principles:

- **Fairness and Non-discrimination**:
    - Foundation model bias assessment across demographic groups
    - MIMIC-IV and PhysioNet dataset diversity analysis
    - Mitigation strategies for population-specific biases
- **Transparency and Explainability**:
    - NeuroKit feature extraction transparency
    - ChatGPT clinical reasoning interpretability
    - End-to-end explanation pipeline validation
- **Accountability and Human Oversight**:
    - Clinician-in-the-loop design with AI-generated reports
    - Foundation model decision boundaries and uncertainty quantification
    - LLM output validation and clinical oversight requirements
- **Privacy and Data Protection**:
    - Patient data handling in NeuroKit processing
    - API security for ChatGPT integration
    - De-identification protocols for clinical features

- **Reliability and Safety**:
  - Foundation model robustness across datasets
  - LLM hallucination mitigation in clinical contexts
  - Fail-safe mechanisms for uncertain diagnoses

8. Discussion (1.5 pages)

- **Foundation Model Performance Analysis** (0.5 pages):
  - HuBERT ECG vs ECG Founder comparative strengths
  - Implications of pre-training strategies on clinical tasks
  - Generalization capabilities across MIMIC-IV and PhysioNet datasets
- **Novel Explainability Approach Impact** (0.5 pages):
  - NeuroKit + ChatGPT pipeline effectiveness
  - Clinical feature interpretation quality
  - Comparison with traditional explainability methods (Grad-CAM, SHAP)
  - Potential for clinical adoption and trust building
- **Limitations and Future Directions** (0.5 pages):
  - Foundation model computational requirements
  - LLM API dependency and latency considerations
  - Dataset limitations and generalization concerns
  - Integration challenges in clinical workflows
  - Future work: real-time processing, extended condition coverage

9. Conclusion (0.5 pages)

- Key achievements summary
- Clinical significance
- Contribution to ECG AI diagnosis field

10. References (1-2 pages)

- 40-60 high-quality references
- Recent papers (2020-2025 preferred)
- Mix of medical and AI/ML journals
- Proper IEEE/ACM citation format