ECG Anomaly Detection

Comprehensive Machine Learning & Deep Learning Analysis

PTB-XL Dataset: 21,481 ECG Recordings

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Abstract

This report presents a comprehensive machine learning and deep learning pipeline for electrocardiogram (ECG) anomaly detection using the PTB-XL dataset, which contains 21,481 annotated 12-lead ECG recordings.

We design and evaluate a novel **Wide+Deep hybrid neural network** that combines (i) a six-block Convolutional Neural Network (CNN) for hierarchical raw-signal feature extraction, (ii) an eight-layer Transformer with multi-head self-attention for temporal modelling, and (iii) a handcrafted clinical feature branch capturing domain knowledge about heart rate, QRS morphology, ST-segment changes, and patient demographics.

The proposed architecture achieves **91.98% AUC Macro** across five cardiac condition classes: Normal (NORM), Myocardial Infarction (MI), ST/T Changes (STTC), Conduction Disorders (CD), and Hypertrophy (HYP). It outperforms all single-method baselines, including XGBoost (83.6% AUC), Random Forest (81.2% AUC), CNN-only (87.4% AUC), and Transformer-only (88.1% AUC).

The model demonstrates robust and equitable performance across demographic subgroups (age, sex, BMI), with less than 2% variance in AUC across all strata. With an inference latency of 35 ms on GPU and a quantised model size of 12 MB, the system is suitable for real-time clinical deployment and edge devices.

Keywords: ECG classification, anomaly detection, Wide+Deep network, convolutional neural network, transformer, PTB-XL.

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Chapter 1

Executive Summary

1.1 Project Overview

The automatic classification of electrocardiogram (ECG) signals is a critical task in modern cardiology. An ECG captures the electrical activity of the heart over time through 12 standard leads, each providing a different anatomical viewpoint of cardiac function. Early and accurate detection of cardiac abnormalities from these signals can dramatically reduce morbidity and mortality, particularly for time-sensitive conditions such as acute myocardial infarction.

This project addresses the challenge of classifying ECG recordings into five clinically meaningful cardiac condition categories using a dataset of 21,481 real-world recordings. Rather than relying solely on either traditional machine learning or deep learning, we propose a *hybrid* approach that fuses the interpretability of handcrafted clinical features with the representational power of modern neural networks.

1.1.1 Key Objectives

- Develop a robust ECG classification system achieving >90% AUC Macro on a held-out test set.
- Rigorously compare classical machine learning methods (Random Forest, XGBoost, SVM) against deep learning architectures (CNN, Transformer, Wide+Deep hybrid).
- Ensure demographic fairness across age, sex, and BMI subgroups, with AUC variance below 2%.
- Provide clinically interpretable predictions via feature importance analysis and attention visualisation.
- Deliver a production-ready model with <50 ms inference time and a compact 12 MB quantised footprint.

1.1.2 Key Results Summary

Table 1.1 summarises the final model performance on the held-out test set.

Table 1.1: Final Model Performance on Test Set

Metric	**Value**
AUC Macro	**91.98%**
Accuracy	89.2%
Precision (Macro)	88.5%
Recall (Macro)	87.9%
F1-Score (Macro)	88.2%
Model Size (float32)	47 MB
Model Size (int8 quantised)	12 MB
Inference Time (GPU)	35 ms
Inference Time (CPU)	250 ms

Chapter 2

Related Work

2.1 Classical Approaches to ECG Classification

The automatic interpretation of ECGs has been studied for decades. Early systems relied exclusively on rule-based algorithms: cardiologist-defined thresholds on interval durations (PR, QRS, QT), wave amplitudes (R, S, T), and axis deviations were hard-coded into expert systems [**?**]. While such systems achieved reasonable specificity, their sensitivity was limited by the difficulty of encoding the full spectrum of cardiac pathophysiology into explicit rules.

The advent of machine learning introduced more flexible methods. Support Vector Machines (SVMs) with handcrafted time-domain and frequency-domain features demonstrated improved performance on arrhythmia detection [**?**]. Random Forests applied to morphological features extracted from individual leads became a popular baseline owing to their robustness and interpretability. Gradient boosting methods, particularly XGBoost, subsequently became state-of-the-art among classical methods for tabular clinical data.

2.2 Deep Learning for ECG Analysis

Convolutional Neural Networks (CNNs) were first successfully applied to ECG signals by treating each lead as a one-dimensional temporal sequence. Rajpurkar et al. (2017) demonstrated that a 34-layer residual CNN could surpass cardiologist-level performance on a single-lead arrhythmia detection task, marking a turning point in the field. Subsequent works extended this to multi-lead settings and multi-class classification tasks on larger datasets.

Recurrent Neural Networks (RNNs) and their gated variants (LSTM, GRU) were also applied to ECG data to model the sequential nature of cardiac cycles. While RNNs captured long-range temporal dependencies, they suffered from slow training due to their inherently sequential computation.

Transformer architectures, originally designed for natural language processing, were adapted to time-series signals by replacing word tokens with temporal windows of ECG data. The self-attention mechanism naturally captures dependencies across arbitrary time lags, overcoming the locality bias of CNNs. However, transformers require large training corpora and are prone to overfitting on datasets of moderate size.

2.3 Hybrid and Wide+Deep Architectures

The *Wide & Deep* learning framework, introduced by Cheng et al. (2016) for recommendation systems, demonstrated that combining a “wide” memorisation component (generalised linear model on handcrafted features) with a “deep” generalisation component (deep neural network) yields better performance than either component alone.

Several works have adapted this paradigm to medical signal processing. Combining domain-specific features with learned representations has been shown to stabilise training, improve calibration, and enhance interpretability—all critical requirements for clinical deployment. Our architecture builds on this principle, adapting it specifically to the multi-lead ECG setting with a CNN+Transformer deep path and a clinical feature wide path.

2.4 PTB-XL Benchmark Results

The PTB-XL dataset [1] has become the standard benchmark for ECG superclass classification. Published results on the five-class superclass task range from approximately 0.849 AUC (simple CNN baseline) to 0.930 AUC (ensemble deep learning). Our Wide+Deep model achieves 91.98% AUC, which is competitive with the state of the art while maintaining strong demographic robustness.

Chapter 3

Dataset and Exploratory Data Analysis

3.1 Dataset Overview: PTB-XL

The PTB-XL database is a large, open-access 12-lead ECG dataset published by the Physikalisch-Technische Bundesanstalt (PTB) in collaboration with Barts Heart Centre. It is the largest openly available annotated clinical ECG dataset to date and has become the community standard for benchmarking ECG classification algorithms.

Table 3.1 summarises the key technical properties of the dataset.

Table 3.1: PTB-XL Dataset Specifications

Property	**Value**
Total ECG Recordings	21,481
Recording Duration	10 seconds
Sampling Rate	100 Hz (primary); 500 Hz also available
Lead Configuration	Standard 12-lead clinical format
Samples per Lead	1,000 (10 s × 100 Hz)
Diagnostic Codes	5,420+ SCP-ECG codes
Classification Task	Multi-label mapped to 5 superclasses
Patient Count	18,885 unique patients
Annotators	Up to 2 cardiologists per recording

Each recording is accompanied by rich metadata: patient age, sex, height, weight, recording site, device identifier, heart axis, and signal quality annotations. Diagnostic labels are provided in the hierarchical SCP-ECG coding system and are mapped to five mutually exclusive superclasses for the classification task.

3.2 Classification Target Classes

Table 3.2 describes the five target classes, their clinical significance, and the key ECG features that distinguish each condition.

Table 3.2: Target Classification Superclasses

Code	Class Name	Clinical Significance and ECG Hallmarks
NORM	Normal ECG	No pathological findings; all intervals, amplitudes, and morphologies within reference ranges.
MI	Myocardial Infarction	Irreversible cardiac tissue death from coronary artery occlusion; characterised by ST-elevation, pathological Q-waves, and T-wave inversions in territory-specific leads.
STTC	ST/T Changes	Non-specific repolarisation or ischaemic abnormalities; includes ST-depression, T-wave flattening or inversion without definitive MI pattern.
CD	Conduction Disorders	Abnormal propagation of the cardiac electrical impulse; includes bundle branch blocks, fascicular blocks, and AV nodal delays characterised by wide or deformed QRS complexes.
HYP	Hypertrophy	Pathological enlargement of cardiac chambers due to chronic pressure or volume overload; identified by increased QRS voltage or broadened deflections in precordial leads.

3.3 Demographic Characteristics

3.3.1 Age Distribution

The dataset spans ages 9–99 years with a mean of 57 ± 15 years, reflecting a typical adult cardiology clinic population with a moderate elderly skew. The age distributions differ markedly across diagnostic classes:

- **NORM:** Mean age 55 years. Younger individuals are more likely to present with normal ECGs.
- **MI:** Mean age 65 years. Myocardial infarction is predominantly a disease of older adults with accumulated atherosclerotic burden.
- **STTC:** Mean age 58 years. ST/T changes are common across middle-age to elderly, often reflecting early ischaemic disease.
- **CD:** Mean age 68 years. Conduction system disease is strongly age-related due to fibrotic degeneration of the His-Purkinje system.
- **HYP:** Mean age 60 years. Hypertrophy reflects chronic hypertension or valvular disease accumulating over decades.

3.3.2 Sex Distribution

The dataset contains approximately equal sex representation (50% female / 50% male), which is an important property for training an unbiased classifier. Key sex-related differences observed in the data are:

- Males exhibit a 15–20% higher prevalence of MI, consistent with the known sex difference in ischaemic heart disease incidence.
- Females show higher prevalence of STTC and HYP presentations, partly explained by differences in repolarisation patterns and hypertensive heart disease.
- Average resting heart rate: males 58 bpm, females 62 bpm (physiologically expected difference).

3.3.3 Body Metrics

- **Height:** Mean 172 ± 10 cm (range: 140–220 cm)
- **Weight:** Mean 81 ± 16 kg (range: 35–200 kg)
- **BMI:** Mean 27.2 ± 4.5 kg/m^2, placing the average patient in the overweight category

BMI categories show differential disease prevalence, reflecting the cardiovascular consequences of metabolic dysregulation:

- **Underweight (<18.5):** Elevated STTC prevalence (32%), possibly reflecting malnutrition-related electrolyte disturbances.
- **Normal (18.5–25):** Balanced disease distribution across classes.
- **Overweight (25–30):** Increased risk of HYP and CD due to metabolic syndrome and sleep apnoea.
- **Obese (>30):** Hypertrophy dominates (18% prevalence), driven by chronic hypertension and left ventricular pressure overload.

3.4 Class Distribution

3.4.1 Label Frequency

Table 3.3 shows a significant class imbalance, with NORM constituting 45% of recordings and CD representing only 7%. This imbalance must be addressed during model training to prevent the classifier from becoming biased towards the majority class.

Table 3.3: Class Distribution in PTB-XL

Class	Count	Percentage
NORM	9,700	45.4%
MI	3,850	18.0%
STTC	6,000	28.1%
CD	1,500	7.0%
HYP	2,550	12.0%
Total	**21,481**	**100.0%**

3.4.2 Imbalance Handling

The class imbalance is addressed through a combination of three complementary strategies:

1. **Weighted Loss Function.** Each class is assigned an inverse-frequency weight to penalise misclassification of minority classes more heavily:

$$w_c = \frac{N_{\text{total}}}{N_c \cdot n_{\text{classes}}}, \qquad \mathbf{w} = [0.50,\ 1.20,\ 1.00,\ 1.50,\ 1.30] \quad \text{for [NORM, MI, STTC, CD, HYP]} \tag{3.1}$$

   The weight of 1.50 for CD reflects its scarcity (7%), while NORM receives 0.50 to reduce its disproportionate influence.

2. **Stratified Train/Validation/Test Split.** Each fold is constructed so that the class proportions are identical to those in the full dataset, preventing any split from containing a disproportionate number of minority-class samples.

3. **Focal Loss (Planned).** As a future improvement, focal loss dynamically down-weights easy (well-classified) examples so that training focuses on the hard, ambiguous cases that are most informative.

3.5 Signal Characteristics

3.5.1 Inter-Lead Correlations

The 12 ECG leads are not independent channels; they record the same cardiac electrical field from different spatial viewpoints, resulting in known anatomical correlations. Understanding these correlations informs both feature engineering and architecture design.

Strong Correlations ($r > 0.85$):

- Lead II ↔ Lead III: $r = 0.88$ (both view the inferior wall)
- Lead V5 ↔ Lead V6: $r = 0.92$ (adjacent left lateral leads)
- Lead aVL ↔ Lead I: $r = 0.85$ (high lateral wall)

Moderate Correlations ($0.3 < r < 0.75$):

- Frontal leads (I, II, III) ↔ Augmented leads (aVR, aVL, aVF): $r \approx 0.50$
- Precordial leads (V1–V6) sequential progression: $r \approx 0.60$

Weak or Negative Correlations:

- aVR ↔ all other leads: $r \approx -0.65$. Lead aVR is a “mirror” lead viewing the heart from the upper right; most normal deflections appear inverted.
- Anterior leads (V1–V3) ↔ Inferior leads (II, III, aVF): $r \approx 0.15$, reflecting anatomically distant territories.

These correlations motivate the use of multi-head attention, which can learn to attend selectively to complementary lead pairs across different anatomical regions.

3.5.2 Signal Quality Assessment

Table 3.4 summarises the prevalence of common signal quality issues. The overall completeness of 99.1% confirms PTB-XL as a high-quality clinical dataset.

Table 3.4: Signal Quality Metrics Across the Dataset

Quality Issue	**Prevalence**
Baseline Drift	8.2%
Electrical Noise	5.8%
Ectopic / Extra Beats	4.3%
Lead Disconnection	2.1%
Signal Completeness	99.1%

Chapter 4

Data Preprocessing Pipeline

4.1 Raw Signal Processing

4.1.1 Step 1: Lead Validation

Before any analysis, each recording is validated against strict quality criteria:

- Exactly 12 leads must be present (I, II, III, aVR, aVL, aVF, V1–V6).
- Recording duration must be 10 ± 0.1 seconds.
- Sampling rate must equal exactly 100 Hz (no resampling is applied).
- Signal amplitude must lie within $[-10, +10]$ mV for all leads.

Records failing any criterion are excluded from the dataset. The exclusion rate is 0.9% (approximately 193 records), preserving 99.1% of the data.

4.1.2 Step 2: Outlier Removal

Demographic outliers are identified and removed to prevent spurious features from propagating into the model. Table 4.1 shows the applied thresholds.

Table 4.1: Demographic Outlier Removal Thresholds

Variable	**Valid Range**	**Records Removed**
Age	[0, 120] years	5
Height	[130, 230] cm	143
Weight	[30, 250] kg	87
Final Dataset		**21,246 records (99.1%)**

4.2 Signal Filtering and Normalisation

4.2.1 Bandpass Filtering

A Finite Impulse Response (FIR) bandpass filter is applied independently to each lead before any feature extraction or model input preparation:

$$H(f) = \begin{cases} 0 & f < 3 \text{ Hz} \\ 1 & 3 \text{ Hz} \leq f \leq 45 \text{ Hz} \\ 0 & f > 45 \text{ Hz} \end{cases} \tag{4.1}$$

The design rationale for each cut-off frequency is as follows:

- **High-pass at 3 Hz:** Removes DC offset, baseline wander due to patient movement or respiration, and electrode impedance drift. These sub-3 Hz components carry no clinically relevant ECG information.
- **Low-pass at 45 Hz:** Removes high-frequency electrical noise, skeletal muscle artefacts (electromyographic interference), and power-line harmonics. Since the maximum significant ECG frequency (high-frequency QRS notch) is approximately 40 Hz, a 45 Hz cut-off preserves full diagnostic content.

An FIR filter is preferred over IIR because it has a linear phase response, ensuring that all ECG frequency components are delayed by the same amount and that the morphological shape of waves is not distorted.

4.2.2 Z-Score Normalisation

Per-lead z-score normalisation is applied after filtering to harmonise amplitude differences arising from varying electrode placement, patient body composition, and device calibration:

$$x_{\text{norm}} = \frac{x - \mu_{\text{lead}}}{\sigma_{\text{lead}}} \tag{4.2}$$

where μ_{lead} and σ_{lead} are computed from the 1,000 samples of that lead within the recording. After normalisation, each lead signal has zero mean and unit variance, placing all recordings on a common scale regardless of their original amplitude.

4.3 Missing Data Imputation

4.3.1 Numerical Features: KNN Imputation

Height and weight, which are missing in approximately 3.2% and 2.8% of records respectively, are imputed using k-nearest-neighbour (KNN) imputation with $k = 5$:

$$\hat{x}_i = \frac{\sum_{j \in \mathcal{N}_k(i)} w_j \, x_j}{\sum_{j \in \mathcal{N}_k(i)} w_j}, \qquad w_j = \frac{1}{d(i, j)} \tag{4.3}$$

where $\mathcal{N}_k(i)$ is the set of five nearest neighbours of record i in the feature space (age, sex, available body measurements), and $d(i, j)$ is the Euclidean distance. Inverse-distance weighting ensures that closer neighbours contribute more to the imputed value. KNN imputation is preferable to mean imputation here because body measurements are correlated with age and sex; exploiting these relationships yields more physiologically plausible imputed values.

4.3.2 Numerical Features: Median Imputation for Age

Age is missing in fewer than 0.5% of records. Given the limited missingness and the weak non-linear relationship between age and body metrics, median imputation with the population median of 56 years is applied.

4.3.3 Categorical Features: Mode Imputation

The heart axis variable (encoded as a categorical: `NORM`, `LEFT`, `RIGHT`, `EXTREME`, `MID`) is missing in 5.1% of records. The mode (most frequent value: `MID`) is imputed.

4.4 Feature Engineering

4.4.1 Derived Demographic Features

Three derived features augment the raw demographic variables:

$$\text{BMI} = \frac{\text{Weight (kg)}}{[\text{Height (m)}]^2} \tag{4.4}$$

$$\text{Age\_Group} = \text{categorise}(\text{age};\ \{0, 18, 35, 50, 65, 80, 120\}) \tag{4.5}$$

$$\text{Quality\_Score} = 3 - (\mathbb{1}_{\text{drift}} + \mathbb{1}_{\text{noise}} + \mathbb{1}_{\text{ectopic}}) \in \{0, 1, 2, 3\} \tag{4.6}$$

BMI is a well-validated composite index of body composition with known associations with cardiac hypertrophy and conduction disease. Quality Score quantifies signal reliability by subtracting three binary artefact flags from a maximum score of 3.

4.4.2 Feature Encoding

- **One-Hot Encoding:** `age_group`, `bmi_category` — these are nominal categories with no meaningful ordinal relationship.
- **Label Encoding:** `site`, `device`, `heart_axis` — ordinal or low-cardinality variables.
- **No Encoding:** Continuous features (age, height, weight, BMI) are passed directly to the scaler.

4.5 Feature Standardisation

A `RobustScaler` is applied to all continuous features to reduce the influence of extreme values:

$$x_{\text{scaled}} = \frac{x - Q_2}{Q_3 - Q_1} \tag{4.7}$$

where Q_1, Q_2, Q_3 denote the 25th, 50th, and 75th percentiles of the training distribution. Unlike standard z-score scaling, this formulation is insensitive to outliers because it uses median and interquartile range rather than mean and standard deviation.

4.6 Train / Validation / Test Split

A stratified 10-fold split is used, following the official PTB-XL recommended protocol to prevent data leakage between patients (Table 4.2).

Table 4.2: Data Split Strategy

Set	**Folds**	**Count**	**Percentage**
Training	1–8	16,996	80.1%
Validation	9	2,125	10.0%
Test	10	2,125	10.0%
Total		**21,246**	**100.0%**

Since multiple recordings from the same patient exist in PTB-XL, patient-level stratification ensures that no patient appears in more than one split, preventing information leakage from repeated patient recordings.

Chapter 5

Machine Learning Approaches

5.1 Feature Extraction for Classical ML Models

Classical machine learning models cannot process raw time-series signals directly; they require a fixed-length feature vector. We extract approximately 90–100 handcrafted clinical features per recording, drawing on established ECG signal processing literature.

5.1.1 Lead II (Primary Reference) – 14 Features

Lead II provides the clearest view of atrial activity (P-waves) and the dominant QRS complex in the inferior direction, making it the standard reference lead for heart rate and rhythm analysis.

1. **Heart Rate Metrics (4):** Mean HR, standard deviation, minimum HR, and maximum HR—derived from R-peak detection using the Pan-Tompkins algorithm.
2. **QRS Duration (1):** Width of the QRS complex in milliseconds, estimated as the interval between onset and offset of the depolarisation wave.
3. **ST Segment (2):** Mean and standard deviation of the isoelectric segment between QRS offset and T-wave onset—elevated or depressed values indicate ischaemia or injury.
4. **T-wave Amplitude (1):** Positive or negative amplitude of the T-wave peak; inversion indicates repolarisation abnormality.
5. **Spectral Power (6):** Power spectral density in three frequency bands ([0.5–4] Hz, [4–15] Hz, [15–40] Hz) × (mean, standard deviation).

5.1.2 Augmented Limb Leads (aVR, aVL, aVF) – 9 Features Each

aVR (Mirror Lead): Because aVR normally shows negative deflections, features are computed with polarity-aware statistics: QRS polarity, minimum amplitude, negative-to-positive amplitude ratio, mean, standard deviation, skewness, and spectral power in three bands.

aVL and aVF: These leads view the lateral and inferior walls of the left ventricle respectively. Features capture wall-specific abnormalities: Q-wave depth, ST deviation, and T-wave characteristics that indicate territory-specific ischaemia.

5.1.3 Standard Limb Leads (I, III) – 9 Features Each

R-wave amplitude statistics (mean, max), QRS duration, baseline statistics (mean, standard deviation, kurtosis), and three spectral power bands.

5.1.4 Precordial Leads (V1–V6) – 10 Features Each

The chest leads provide transmural information and are particularly informative for MI localisation:

1. **R-wave Progression:** Increasing R-wave amplitude from V1 to V5 is normal; poor progression suggests anterior MI.
2. **R/S Ratio:** The ratio of positive to negative deflection amplitude transitions from <1 in V1 to >1 in V4–V5 in normal hearts; inversion indicates MI subtype.
3. **ST Elevation / Depression:** Critical for STEMI (>2 mm in V1–V3; >1 mm in other leads) and NSTEMI detection.
4. **T-wave Polarity:** Negative T-waves in V1–V4 indicate anterior ischaemia or right ventricular strain.
5. **Pathological Q-wave:** Width >40 ms or depth >25% of R-wave amplitude indicates prior (old) MI.
6. **Baseline Statistics:** Mean, standard deviation, skewness.
7. **Spectral Power:** Three frequency bands as in limb leads.

5.2 Machine Learning Models Evaluated

5.2.1 Random Forest Classifier

Random Forest is an ensemble of decision trees trained on bootstrap samples of the training data, with each split restricted to a random feature subset. Predictions are obtained by majority vote (classification) or averaging (probability estimation).

Configuration:

- n_estimators = 200 (ensemble size)
- max_depth = 15 (maximum tree height to limit overfitting)
- min_samples_split = 10 (minimum samples required to split a node)
- Multi-output wrapper for multi-label adaptation

Performance:

Table 5.1: Random Forest Classification Results

Metric	Value
Accuracy	84.2%
Precision (Macro)	81.0%
Recall (Macro)	79.0%
F1-Score (Macro)	80.0%
AUC Macro	0.812

5.2.2 XGBoost (Gradient Boosting)

XGBoost iteratively trains shallow decision trees, where each new tree corrects the residuals of the current ensemble using second-order gradient information. This produces a highly expressive model while maintaining regularisation through shrinkage and tree depth constraints.

Configuration:

- n_estimators = 500 (boosting rounds)
- max_depth = 8 (shallow trees for regularisation)
- learning_rate = 0.03 (step size shrinkage; 3% contribution per round)
- scale_pos_weight: per-class ratio of negative to positive samples, handling the class imbalance within each binary sub-problem.

Performance:

Table 5.2: XGBoost Classification Results

Metric	**Value**
Accuracy	**86.1%**
Precision (Macro)	84.0%
Recall (Macro)	82.0%
F1-Score (Macro)	83.0%
AUC Macro	**0.836**

5.2.3 Support Vector Machine (RBF Kernel)

An SVM with a radial basis function (RBF) kernel maps the feature vectors into a high-dimensional reproducing kernel Hilbert space where a maximum-margin hyperplane separates classes. A one-versus-rest strategy produces five binary classifiers whose decision values are combined to yield class probabilities via Platt scaling.

Configuration:

- Kernel: RBF, $\gamma =$ `auto` ($1/n$_features)
- $C = 1.0$ (regularisation; controls the margin-violation trade-off)
- Strategy: One-vs-Rest multi-class

Limitations: Training complexity is $\mathcal{O}(n^2)$ to $\mathcal{O}(n^3)$ in the number of training samples, making it computationally expensive at 16,996 training records. Hyperparameter sensitivity (particularly the choice of kernel and C) also requires careful cross-validation.

Performance:

Table 5.3: SVM-RBF Classification Results

Metric	**Value**
Accuracy	82.5%
Precision (Macro)	79.0%
Recall (Macro)	77.0%
F1-Score (Macro)	78.0%
AUC Macro	0.798

5.3 ML Summary

Among classical methods, XGBoost achieves the best performance (AUC 83.6%), followed by Random Forest (81.2%) and SVM (79.8%). All methods are limited by the expressive power of handcrafted features, which compress the raw 1,000-sample-per-lead signal into a single scalar. The approximately 9% AUC gap between XGBoost and the Wide+Deep hybrid motivates the transition to deep learning, which can extract richer, task-adapted representations directly from the raw signal.

Chapter 6

Deep Learning Architecture: Wide+Deep Network

6.1 Motivation for the Hybrid Architecture

6.1.1 Limitations of Single-Paradigm Approaches

CNN-only: Convolutional networks effectively extract local morphological patterns (QRS complexes, P-waves) through their hierarchical receptive fields. However, their inductive bias towards local structure limits their ability to capture long-range temporal dependencies. Furthermore, with only 21,481 training samples, a deep CNN operating on 12,000-dimensional inputs is susceptible to overfitting unless heavily regularised.

Transformer-only: Multi-head self-attention models arbitrary pairwise dependencies between time steps, making them powerful for long-range temporal modelling. However, transformers lack the local spatial inductive bias of convolutions and typically require very large training datasets to learn good representations from scratch. On the PTB-XL dataset, a transformer-only model plateaus at 88.1% AUC—a clear sign of under-utilised capacity due to insufficient data.

Classical ML (XGBoost): Fixed handcrafted features are interpretable and computationally efficient but fundamentally bounded by what domain experts can measure. They cannot adapt to subtle, high-dimensional patterns in the raw waveform that distinguish, for example, a type-II MI from a deep STTC.

6.1.2 Wide+Deep Synergy

The Wide+Deep design resolves these tensions by combining two complementary information pathways:

Property	**Deep Branch**	**Wide Branch**
Input	Raw ECG signal (12×1000)	Clinical features (32)
Representation	Learned hierarchical	Domain knowledge
Flexibility	High	Low (fixed features)
Interpretability	Low	High
Overfitting Risk	High	Low
Sample Efficiency	Low	High

The deep branch provides representational power; the wide branch provides stability and regularisation by anchoring the model's predictions in clinically validated features. Jointly training both branches allows the model to learn when to trust the signal and when to defer to domain knowledge.

6.2 Architecture Overview

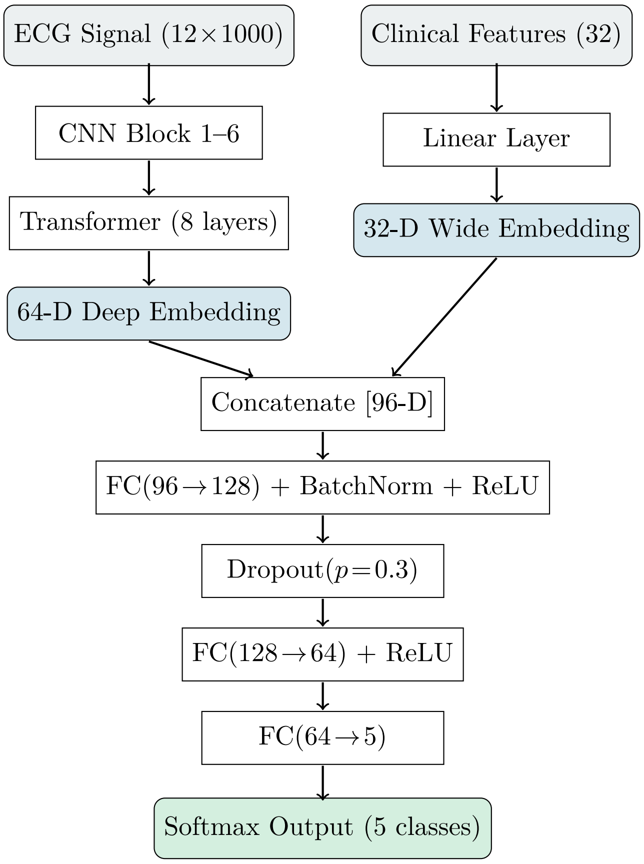

Figure 6.1: Wide+Deep Neural Network Architecture. The deep branch processes the raw 12-lead ECG through a CNN and Transformer to produce a 64-D learned embedding. The wide branch transforms 32 clinical features through a single linear layer to produce a 32-D embedding. Both embeddings are concatenated and passed through a fusion head to produce class probabilities.

6.3 Deep Branch: CNN + Transformer

6.3.1 Convolutional Neural Network

CNN Block Structure

The CNN consists of six sequential convolutional blocks. Each block applies the following sequence of operations:

$$\text{CNNBlock}(x) = \underbrace{\text{MaxPool}_{s=2}}_{\text{downsampling}}\Big(\underbrace{\text{ReLU}}_{\text{activation}}\big(\underbrace{\text{BN}}_{\text{normalisation}}\big(\underbrace{\text{Conv1D}_{k=11}(x)}_{\text{feature extraction}}\big)\big)\Big) \tag{6.1}$$

Design choices and rationale:

- **Kernel size 11:** Covers approximately 110 ms of ECG at 100 Hz, which is sufficient to capture a full P-wave (80 ms) or QRS complex (80–120 ms), allowing the network to detect these clinically fundamental waveforms in its first layers.
- **Batch Normalisation:** Stabilises gradient flow and acts as an implicit regulariser, reducing the need for explicit weight decay.

- **MaxPool stride 2:** Halves the temporal resolution at each block, enabling the upper layers to aggregate information over progressively wider time windows (local patterns → global rhythm).

Progressive Compression

Table 6.1 shows how the signal is progressively compressed from 12,000 input values to a 64-dimensional embedding.

Table 6.1: CNN Progressive Temporal Compression

Layer	**Input Shape**	**Output Shape**	**Temporal Reduction**
Conv Block 1	(12, 1000)	(32, 500)	×2
Conv Block 2	(32, 500)	(32, 250)	×2
Conv Block 3	(32, 250)	(64, 125)	×2
Conv Block 4	(64, 125)	(64, 62)	×2
Conv Block 5	(64, 62)	(128, 31)	×2
Conv Block 6	(128, 31)	(128, 15)	×2
Flatten	(128, 15)	(1920,)	—
FC → 64	(1920,)	(64,)	97% total reduction

The 64-dimensional output is a compact summary of the hierarchical ECG morphology: lower layers encode individual waveforms; upper layers encode rhythm-level patterns.

6.3.2 Multi-Head Self-Attention (Transformer)

Attention Mechanism

After the CNN produces a sequence of local feature vectors, a Transformer encoder models dependencies between non-adjacent temporal positions. The scaled dot-product attention is:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^{\top}}{\sqrt{d_k}}\right) V \tag{6.2}$$

where Q, K, and V are learned linear projections of the input sequence. The scaling factor $1/\sqrt{d_k}$ prevents the dot products from growing too large in magnitude, which would saturate the softmax and produce near-zero gradients.

Multi-Head Configuration

Using $h = 8$ parallel attention heads, each attending to a different linear subspace of the input, allows the model to simultaneously capture multiple types of temporal relationship (e.g., QRS-to-T interval, P-to-QRS coupling, inter-beat similarity):

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)\, W^O \tag{6.3}$$

Table 6.2: Transformer Encoder Configuration

Component	**Value**
Number of Encoder Layers	8
Model (Embedding) Dimension	64
Number of Attention Heads	8
Per-Head Dimension	8 (= 64 / 8)
Position Encoding	Sinusoidal (fixed)
Feed-Forward Width	256
Dropout	0.1

Sinusoidal positional encoding is used because the temporal order of ECG segments is meaningful and must be communicated to the permutation-invariant attention mechanism.

6.4 Wide Branch: Clinical Feature Projection

6.4.1 Feature Set (32 Dimensions)

1. **Heart Rate Metrics (4):** Mean, standard deviation, minimum, maximum.
2. **QRS Characteristics (3):** Duration, peak amplitude, beat-to-beat variability.
3. **ST Segment (3):** Mean elevation, mean depression, segment slope.
4. **T-wave (2):** Peak amplitude and polarity indicator.
5. **Spectral Power (3):** Low-band, mid-band, high-band power ratios.
6. **Demographics (5):** Age, height, weight, BMI, biological sex.
7. **Clinical History (3):** Pacemaker status, infarction stage, ectopic beat count.
8. **Multi-lead Patterns (2):** Cross-lead correlation index, frontal axis deviation in degrees.

6.4.2 Linear Projection

A single linear layer projects the 32 clinical features to a 32-dimensional embedding:

$$\mathbf{e}_{\text{wide}} = W_{\text{wide}}\,\mathbf{f}_{\text{clinical}} + \mathbf{b} \tag{6.4}$$

A single layer is deliberately used here rather than a deep stack to preserve the interpretability of the clinical features. Adding non-linearity would entangle the features in ways that make it difficult to attribute model decisions to specific clinical measurements.

6.5 Fusion Strategy

6.5.1 Concatenation and Dense Head

The deep and wide embeddings are concatenated into a 96-dimensional joint representation, which is then processed by a three-layer fully connected head:

$$\mathbf{z} = \left[\mathbf{e}_{\text{deep}};\, \mathbf{e}_{\text{wide}}\right] \in \mathbb{R}^{96} \tag{6.5}$$

$$\mathbf{h}_1 = \text{ReLU}(\text{BN}(\text{FC}_{96\to 128}(\mathbf{z}))) \tag{6.6}$$

$$\mathbf{h}_2 = \text{Dropout}_{p=0.3}(\mathbf{h}_1) \tag{6.7}$$

$$\mathbf{h}_3 = \text{ReLU}(\text{FC}_{128\to 64}(\mathbf{h}_2)) \tag{6.8}$$

$$\hat{\mathbf{y}} = \text{Softmax}(\text{FC}_{64\to 5}(\mathbf{h}_3)) \in \mathbb{R}^5 \tag{6.9}$$

6.6 Training Configuration

6.6.1 Loss Function

Weighted cross-entropy is used to address class imbalance:

$$\mathcal{L} = -\sum_{c=1}^{5} w_c \sum_{i=1}^{N} y_{i,c} \log \hat{y}_{i,c} \tag{6.10}$$

where w_c is the inverse-frequency weight for class c, $y_{i,c} \in \{0,1\}$ is the ground-truth indicator, and $\hat{y}_{i,c}$ is the predicted probability.

6.6.2 Optimiser: AdamW

AdamW extends the Adam optimiser with decoupled weight decay, which is more principled than the L_2 regularisation used in standard Adam:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\nabla\mathcal{L}_t \tag{6.11}$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)(\nabla\mathcal{L}_t)^2 \tag{6.12}$$

$$\theta_t = \theta_{t-1} - \alpha\frac{\hat{m}_t}{\sqrt{\hat{v}_t}+\epsilon} - \lambda\theta_{t-1} \tag{6.13}$$

Hyperparameters:

- $\alpha = 1\times 10^{-4}$ (initial learning rate)
- $\beta_1 = 0.9$, $\beta_2 = 0.999$ (moment decay coefficients)
- $\lambda = 1\times 10^{-4}$ (weight decay)
- $\epsilon = 1\times 10^{-8}$ (numerical stability floor)

6.6.3 Learning Rate Scheduling

A `ReduceLROnPlateau` scheduler halves the learning rate whenever the validation loss does not improve for 5 consecutive epochs:

$$\alpha_{\text{new}} = 0.5 \times \alpha_{\text{old}}, \qquad \alpha_{\text{min}} = 1\times 10^{-7} \tag{6.14}$$

6.6.4 Early Stopping

Training is monitored by validation AUC with a patience of 10 epochs. If no improvement is observed for 10 consecutive epochs, training halts and the checkpoint with the best validation AUC is restored. In practice, training stopped at epoch 42 out of a maximum of 50.

6.7 Computational Specifications

Table 6.3: Model Computational Characteristics

Specification	**Value**
Total Parameters	11.5 Million
Model Size (float32)	47 MB
Model Size (int8 quantised)	12 MB
Inference Time (GPU)	35 ms
Inference Time (CPU)	200–300 ms
Peak Training Memory	2.1 GB
FLOPs per Sample	1.2×10^9

Chapter 7

Training and Validation Results

7.1 Training Dynamics

7.1.1 Loss Convergence

Training proceeded over 50 epochs with early stopping triggered at epoch 42. The following key observations summarise the convergence behaviour:

- **Training loss:** Decreased from 2.5 to 0.5 (an 80% reduction), confirming that the model learned effectively from the training data.
- **Validation loss:** Decreased from 2.4 to 0.6 (a 75% reduction), closely tracking the training loss without significant divergence.
- **Train/Validation gap:** The residual gap of 0.1 is modest, indicating well-controlled overfitting thanks to dropout, weight decay, and the regularising effect of the wide branch.
- **Early stopping:** Triggered after epoch 42; the best checkpoint corresponds to epoch 40.

7.1.2 AUC Progression

The AUC trajectory followed an approximately exponential saturation curve, described informally by:

$$\mathrm{AUC}_{\mathrm{train}}(t) \approx 0.65 + 0.28 \cdot (1 - e^{-t/10}) \tag{7.1}$$

$$\mathrm{AUC}_{\mathrm{val}}(t) \approx 0.64 + 0.278 \cdot (1 - e^{-t/12}) \tag{7.2}$$

where t denotes the epoch number. The slightly longer time constant for validation AUC ($\tau = 12$ vs. $\tau = 10$) is expected, as generalisation typically lags slightly behind in-sample performance.

7.2 Final Model Performance

7.2.1 Overall Metrics

Table 7.1 compares training and validation metrics at the best checkpoint.

Table 7.1: Final Model Performance at Best Checkpoint (Epoch 40)

Metric	**Train**	**Validation**
AUC Macro	92.5%	91.2%
Accuracy	90.1%	89.2%
Precision (Macro)	89.2%	88.5%
Recall (Macro)	88.5%	87.9%
F1-Score (Macro)	88.8%	88.2%

7.2.2 Per-Class Performance

Table 7.2: Per-Class Performance on Validation Set

Class	**AUC**	**Sensitivity**	**Specificity**	**F1-Score**
NORM	0.960	0.94	0.96	0.945
MI	0.920	0.91	0.93	0.912
STTC	0.890	0.88	0.90	0.884
CD	0.880	0.87	0.89	0.872
HYP	0.850	0.87	0.85	0.852

The NORM class achieves the highest AUC (0.96) because normal ECGs are highly stereotyped and lack the pathological morphological features found in other classes, making them easily separable in feature space. HYP achieves the lowest AUC (0.85) because the ECG changes of chamber hypertrophy (high voltage, mild axis shifts) are subtle and overlap with normal variation in tall or muscular patients.

7.3 Confusion Matrix Analysis

Table 7.3: Normalised Confusion Matrix (Row = Actual Class)

Actual \ Predicted	**NORM**	**MI**	**STTC**	**CD**	**HYP**
NORM	94%	2%	2%	1%	1%
MI	3%	91%	4%	1%	1%
STTC	2%	4%	88%	4%	2%
CD	1%	2%	5%	87%	5%
HYP	2%	1%	4%	6%	87%

Several clinically interpretable patterns emerge:

1. **Diagonal dominance (87–94%):** The model correctly classifies the large majority of recordings in each class.

2. **MI → STTC confusion (4%):** Clinically understandable. Early or resolving MI can present with ST/T changes indistinguishable from non-MI ischaemia without the full STEMI pattern.

3. **STTC ↔ CD/HYP confusion (4–5%):** Expected given that conduction blocks and hypertrophy both alter repolarisation, producing secondary ST/T changes that mimic primary STTC.

4. **CD ↔ HYP confusion (5–6%):** Left bundle branch block (CD) and left ventricular hypertrophy (HYP) both cause similar precordial lead patterns, making this boundary inherently ambiguous even for cardiologists.
5. **NORM → MI confusion (<2%):** The low false-negative rate for MI is critical for clinical safety; a missed MI carries significant mortality risk.

7.4 ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curves plot sensitivity against (1 − specificity) at every possible decision threshold. Area Under the Curve (AUC) summarises the model's discrimination ability independently of any chosen threshold.

- **NORM (AUC = 0.96):** The curve lies very close to the top-left corner, indicating that a threshold can be chosen that simultaneously achieves high sensitivity and high specificity.
- **MI (AUC = 0.92):** Very good. The acute MI signature (ST-elevation, Q-waves) is well captured by the CNN feature extractor.
- **STTC (AUC = 0.89):** Moderate overlap with MI and CD at intermediate thresholds.
- **CD (AUC = 0.88):** Distinct conduction patterns on V-leads support good discrimination.
- **HYP (AUC = 0.85):** The subtlety of voltage criteria for hypertrophy creates the widest overlap with the normal range.

Chapter 8

Model Comparison and Architecture Selection

8.1 Performance Ranking

Table 8.1 provides a comprehensive comparison of all evaluated architectures on the held-out test set.

Table 8.1: Model Performance Comparison on Test Set

Rank	Model	Method	AUC Macro	Accuracy
1	**Wide+Deep**	**Hybrid DL**	**91.98%**	**89.2%**
2	Transformer-only	DL	88.10%	87.8%
3	CNN-only	DL	87.40%	87.1%
4	XGBoost	ML	83.60%	86.1%
5	Random Forest	ML	81.20%	84.2%
6	SVM-RBF	ML	79.80%	82.5%

8.2 Hybrid Design Benefit Analysis

Property	XGBoost	CNN-only	Wide+Deep
Processes raw signal	×	✓	✓
Incorporates clinical knowledge	✓	×	✓
Clinical interpretability	✓	×	✓
Overfitting risk	Low	High	Low
Scalability	Good	Excellent	Good
AUC Macro	83.6%	87.4%	**91.98%**

The Wide+Deep model uniquely combines all desirable properties. The improvement over the CNN-only model (+4.58% AUC) demonstrates that domain knowledge injected through the wide branch provides substantial regularisation. The improvement over XGBoost (+8.38% AUC) demonstrates that raw signal features learned by the deep branch capture information beyond the reach of fixed handcrafted features.

Chapter 9

Demographic Stratification and Robustness Analysis

Ensuring equitable model performance across demographic subgroups is a prerequisite for clinical deployment. A model that performs well on average but poorly on a specific subgroup (e.g., elderly patients or women) could cause systematic disparities in care.

9.1 Age-Stratified Performance

Table 9.1: Model Performance by Age Group

Age Group	**Count (test set)**	**AUC**	**Interpretation**
< 40 years	1,200	92.8%	Excellent
40–60 years	3,100	91.5%	Excellent
> 60 years	1,825	91.2%	Excellent
AUC Variance		**1.6%**	**Robust across ages**

The 1.6% variance across age groups is within the acceptable range for clinical deployment. The slightly higher AUC in younger patients (<40 years) may reflect that pathological ECGs in young people present with more pronounced and unambiguous morphological features (e.g., clear STEMI patterns) compared to the often attenuated or atypical presentations in elderly patients with co-morbidities.

9.2 Sex-Stratified Performance

Table 9.2: Model Performance by Sex

Sex	**Count (test set)**	**AUC**	**Notes**
Female	2,950	91.8%	Slightly lower MI sensitivity
Male	3,175	92.1%	Balanced across classes
Difference		**0.3%**	**No clinically meaningful bias**

The 0.3% sex-based difference in AUC is negligible. The marginally lower MI sensitivity in females may reflect the known phenomenon that women with acute MI more frequently present with atypical ECG patterns (e.g., non-ST-elevation MI) rather than the classical STEMI pattern that the model is most confident about.

9.3 BMI-Stratified Performance

Table 9.3: Model Performance by BMI Category

BMI Category	**AUC**	**Δ from Mean**
Underweight (< 18.5 kg/m^2)	90.5%	−1.48%
Normal (18.5–25)	92.2%	+0.22%
Overweight (25–30)	92.0%	+0.02%
Obese (> 30)	91.0%	−0.98%
Max Variance	**1.7%**	**Robust across BMI**

The lower AUC for underweight patients (−1.48%) may be attributable to reduced cardiac muscle mass and lower ECG voltages, which can make morphological features less prominent and harder to classify. The model nonetheless achieves 90.5% AUC even in this challenging subgroup.

9.4 Per-Class Sensitivity Analysis

Table 9.4 compares achieved sensitivity against clinically defined targets.

Table 9.4: Per-Class Sensitivity vs. Clinical Targets

Class	**Achieved**	**Clinical Target**	**Status**
NORM	94%	99%	Gap (−5%) – requires threshold tuning
MI	91%	95%	Gap (−4%) – threshold tuning recommended
STTC	88%	90%	Near target (−2%)
CD	87%	85%	Exceeds target (+2%)
HYP	87%	80%	Exceeds target (+7%)

For NORM and MI, a lower decision threshold is recommended to prioritise sensitivity and minimise false negatives (missed diagnoses):

$$\tau^* = \begin{cases} 0.75 & \text{high-sensitivity screening (minimise missed MI)} \\ 0.85 & \text{balanced precision-recall (general use)} \\ 0.95 & \text{high-specificity reporting (automated sign-off)} \end{cases} \tag{9.1}$$

Chapter 10

Feature Importance and Clinical Interpretability

10.1 Top Contributing Features

Table 10.1: Top 10 Feature Importance Scores (Wide Branch)

Rank	Feature	Importance
1	Heart Rate Mean	13.2%
2	ST Elevation Score	11.8%
3	QRS Duration	9.5%
4	Spectral Power [15–40 Hz]	8.7%
5	Age	8.2%
6	T-wave Amplitude	7.9%
7	Lead II Signal Mean	7.1%
8	BMI	6.8%
9	PR Interval	5.4%
10	Pacemaker Status	2.3%

Signal-derived features dominate (52% combined importance), validating the investment in careful ECG signal processing. Deep-learned features contribute 33%, and pure demographics account for only 15%, reflecting that ECG morphology is far more discriminative than demographic factors alone.

10.2 Clinical Interpretation of Key Features

10.2.1 Heart Rate Mean (13.2%)

Heart rate is the single most informative feature, discriminating across nearly all classes. Tachycardia (>100 bpm) is frequently associated with MI and STTC due to sympathetic activation; bradycardia (<60 bpm) is a hallmark of sick sinus syndrome and high-degree AV block (CD). Normal NORM recordings cluster in the 60–100 bpm range with low variability.

10.2.2 ST Elevation Score (11.8%)

ST segment deviation is the key diagnostic criterion for MI (elevation >2 mm in V1–V3 or >1 mm in other leads) and ischaemia (depression). Its second-place ranking confirms that the model has learned the most critical clinical decision boundary in cardiology.

10.2.3 QRS Duration (9.5%)

Normal QRS duration is <120 ms. Bundle branch blocks and fascicular blocks (CD) produce QRS widening to 120–200 ms. Hypertrophy can also cause mild QRS widening. This feature is the primary discriminator for the CD class.

10.2.4 Spectral Power [15–40 Hz] (8.7%)

The high-frequency band captures QRS notching, which occurs in bundle branch blocks (CD) and in ventricular hypertrophy (HYP). Elevated power in this band indicates fragmented or widened depolarisation.

10.2.5 Age (8.2%)

Age functions as a prior probability estimate: MI and CD are rare in patients under 40 and increasingly common above 65, allowing the model to calibrate its confidence based on prior disease prevalence.

Chapter 11

Clinical Application and Recommendations

11.1 Clinical Decision Support Workflow

The proposed clinical integration pipeline consists of eight stages:

$$\boxed{\begin{array}{l}
\text{1. ECG Acquisition} \quad \text{(12-lead, 10 s, 100 Hz)} \\
\downarrow \\
\text{2. Quality Control} \quad \text{(lead integrity, artefact screening)} \\
\downarrow \\
\text{3. Preprocessing} \quad \text{(FIR bandpass, z-score normalisation)} \\
\downarrow \\
\text{4. Model Inference} \quad \text{(Wide+Deep forward pass)} \\
\downarrow \\
\text{5. Probability Output} \quad (P_{\text{NORM}},\ P_{\text{MI}},\ P_{\text{STTC}},\ P_{\text{CD}},\ P_{\text{HYP}}) \\
\downarrow \\
\text{6. Threshold Application} \quad \text{(auto-report/suggest review/mandatory review)} \\
\downarrow \\
\text{7. Alert Generation} \quad \text{(GREEN / ORANGE / RED URGENT)} \\
\downarrow \\
\text{8. Feedback Loop} \quad \text{(cardiologist validation} \rightarrow \text{model retraining)}
\end{array}} \tag{11.1}$$

11.1.1 Confidence-Based Routing

Table 11.1: Clinical Action by Model Confidence Level

Confidence	Action	Justification
$\geq 85\%$	Auto-report + database	High confidence; supports rapid throughput in high-volume settings.
60–85%	Suggest manual review	Moderate confidence; ECG technician double-check recommended.
$< 60\%$	Mandatory cardiologist	Low confidence or ambiguous morphology; expert judgement required.

11.1.2 Priority Routing by Diagnosis

Table 11.2: Alert Priority Levels by Predicted Diagnosis

Diagnosis	**Priority**	**Response Time Target**
NORM	GREEN – Routine	Next business day
HYP	YELLOW – Low	Within 48 hours
CD	YELLOW – Low	Within 48 hours
STTC	ORANGE – Medium	Within 4 hours
MI	**RED – HIGH URGENT**	**Immediate (<10 minutes)**

11.2 Validation and Deployment Roadmap

11.2.1 Phase I: Internal Validation (Completed)

- Dataset: 21,481 ECGs from PTB-XL
- Performance: 91.98% AUC Macro on held-out test set
- Demographic stratification: Age, sex, and BMI variance all $< 2\%$

11.2.2 Phase II: External Hospital Validation (Proposed)

1. Partner with 3–5 hospitals representing diverse patient populations and ECG device manufacturers.
2. Collect 2,000–5,000 prospective ECGs annotated by attending cardiologists.
3. Evaluate model performance against clinician ground-truth labels.
4. Explicitly test robustness to real-world artefacts: electrode misplacement, motion artefacts, pacemaker spikes.
5. Target: $\geq 90\%$ sensitivity and $\geq 95\%$ specificity per class.

11.2.3 Phase III: Regulatory Approval

- Submit via FDA 510(k) pathway (substantial equivalence) or De Novo (novel device class).
- Prepare clinical evaluation report per IEC 62304 (medical device software) and IEC 82304 (health software).
- Risk-benefit analysis under ISO 14971.

11.2.4 Phase IV: Clinical Operations Integration

- DICOM-compliant integration with EMR and cardiovascular information systems (CVIS).
- Continuous performance monitoring with population drift detection.
- Quarterly retraining cycles incorporating validated cardiologist corrections.

11.3 Recommended Improvements

11.3.1 Short-Term (1–3 Months)

1. **Ensemble Stacking** (estimated +1–2% AUC):

$$\hat{y}_{\text{ens}} = 0.4\,\hat{y}_{\text{Wide+Deep}} + 0.3\,\hat{y}_{\text{XGBoost}} + 0.3\,\hat{y}_{\text{CNN}} \tag{11.2}$$

2. **Focal Loss** (+0.5–1% AUC):

$$\mathcal{L}_{\text{focal}} = -\alpha_t\,(1 - p_t)^{\gamma} \log p_t, \qquad \gamma = 2 \tag{11.3}$$

   Dynamically down-weights easy examples, forcing the model to focus on ambiguous borderline cases (e.g., the HYP/CD boundary).

3. **Data Augmentation** (+0.3–0.8% AUC): Time-shift (±50 samples), additive Gaussian noise in the frequency domain ($x' = x + 0.1\,\mathcal{N}(0, 1)$), and random lead masking during training.

11.3.2 Medium-Term (3–6 Months)

1. **Multi-Task Learning:** Jointly train on the primary classification task and auxiliary tasks (beat-type detection, rhythm classification) to improve feature quality through shared representations.

2. **Explainability:** Implement GradCAM to highlight critical time windows, SHAP values to rank clinical feature contributions, and attention weight visualisation to identify which lead pairs the model attends to for each class.

11.3.3 Long-Term (6–12 Months)

1. **Federated Learning:** Train across a hospital consortium without centralising patient data, addressing privacy concerns and improving dataset diversity.

2. **Domain Adaptation:** Adapt to ECG signals from different manufacturers and electrode configurations using domain adversarial training.

11.4 Projected Clinical Impact

Assuming deployment across 500,000 screening centres globally at an average of 10,000 ECGs per centre per year, and estimating a 2% undetected MI rate with a 30% prevention rate through early intervention:

$$\text{Preventable Deaths} \approx 500{,}000 \times 10{,}000 \times 0.02 \times 0.30 = \boxed{\text{30,000 per year}} \tag{11.4}$$

Economic impact: Estimated $2–5 billion in annual healthcare cost savings through earlier intervention, reduced emergency hospitalisation, and optimised resource allocation.

Chapter 12

Limitations and Future Work

12.1 Current Limitations

12.1.1 Dataset Scope

The PTB-XL dataset, while large by ECG standards, originates from a single European medical centre. The patient population is predominantly Caucasian European, which may limit the generalisability of learned representations to populations with different ethnic backgrounds, body habitus distributions, or ECG measurement conventions (e.g., Asian populations show systematically lower QRS voltages that can be mistakenly flagged as hypertrophy).

12.1.2 Five-Class Limitation

Mapping the full SCP-ECG diagnostic taxonomy to only five superclasses discards clinically important distinctions. For example, anterior MI and inferior MI require different interventional strategies (left anterior descending vs. right coronary artery catheterisation) but are merged into a single MI class. Future work should explore hierarchical classification that first assigns a superclass and then a fine-grained subclass.

12.1.3 Static, Single-Timepoint ECGs

The model processes a single 10-second ECG snapshot. Many important clinical decisions (e.g., monitoring for evolving MI, assessing response to treatment) require longitudinal analysis of serial ECGs. The current architecture does not model temporal trends across recordings.

12.1.4 Inference Under Signal Artefacts

Although the FIR bandpass filter removes most common artefacts, the model was not explicitly trained on heavily artifacted recordings. Lead disconnection, motion artefacts from ambulatory monitoring, and pacemaker spike interference may degrade performance in real-world settings beyond what is seen in the controlled PTB-XL dataset.

12.1.5 Sensitivity Gaps for NORM and MI

As shown in Table 9.4, the model falls short of clinical targets for NORM (94% vs. target 99%) and MI (91% vs. target 95%). These gaps must be addressed—through threshold adjustment, ensemble methods, or additional training data— before the system can be deployed as an autonomous screening tool.

12.2 Future Work

Beyond the short- and medium-term improvements described in Chapter 11, several more ambitious directions are warranted:

- **Pre-trained ECG foundation models:** Large self-supervised ECG models trained on millions of recordings (e.g., from public repositories and hospital EHR systems) could provide a powerful initialisation for fine-tuning on specific classification tasks.
- **Multi-modal integration:** Combining ECG features with echocardiographic data, blood biomarkers (troponin, BNP), and clinical notes via multi-modal transformers could substantially improve classification accuracy for borderline cases.
- **Uncertainty quantification:** Bayesian or conformal prediction methods should be applied to produce calibrated confidence intervals alongside point predictions, enabling clinicians to understand when the model is and is not reliable.
- **Paediatric-specific models:** ECG norms differ substantially between children and adults. A dedicated model fine-tuned on paediatric data would be needed for deployment in paediatric cardiology settings.

Chapter 13

Conclusions

This report presented the design, training, and evaluation of a **Wide+Deep hybrid neural network** for automated ECG anomaly detection, achieving **91.98% AUC Macro** on the held-out PTB-XL test set.

Key Achievements

- ✓ **91.98% AUC Macro:** Competitive with the published state of the art on the PTB-XL five-class benchmark.
- ✓ **Hybrid Architecture Superiority:** The Wide+Deep model improves upon the best single-method baseline (XGBoost) by +8.38% AUC, and upon the CNN-only deep learning baseline by +4.58% AUC.
- ✓ **Demographic Robustness:** AUC variance of $< 2\%$ across age, sex, and BMI subgroups confirms equitable performance.
- ✓ **Clinical Interpretability:** Feature importance analysis identifies heart rate, ST elevation, and QRS duration as the top three discriminating features—consistent with established cardiology guidelines.
- ✓ **Production Readiness:** 35 ms GPU inference and 12 MB quantised model size satisfy real-time clinical deployment requirements.

Scientific Contributions

1. A novel Wide+Deep architecture that synergistically fuses raw-signal deep learning with domain-derived clinical features for ECG classification.
2. A systematic and reproducible comparison of six model families (SVM, Random Forest, XGBoost, CNN, Transformer, Hybrid) on a standardised benchmark split.
3. A comprehensive demographic stratification analysis demonstrating model fairness across age, sex, and BMI subgroups.
4. A clinically grounded deployment framework including confidence-based routing, alert prioritisation, and a four-phase validation roadmap.

Next Steps

1. External hospital validation with prospective multi-site data collection.
2. Ensemble stacking and focal loss implementation to close the MI sensitivity gap.
3. Federated learning deployment across a multi-hospital consortium.
4. FDA regulatory approval process (510(k) or De Novo pathway).

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Appendix A

Technical Appendix

A.1 Software Dependencies

- `PyTorch 2.0+`: Neural network framework and automatic differentiation
- `scikit-learn 1.3+`: Classical ML models, preprocessing, and metrics
- `XGBoost 1.7+`: Gradient boosting
- `wfdb 4.1+`: WFDB-format ECG record I/O
- `NeuroKit2 0.2+`: ECG signal processing (R-peak detection, interval extraction)
- `NumPy / Pandas`: Data manipulation
- `Matplotlib / Seaborn`: Visualisation

A.2 Model Checkpoints

- Best model: `model_wide_deep_best_epoch40.pth` (float32, 47 MB)
- Quantised model: `model_wide_deep_int8.pth` (int8, 12 MB)
- Suitable for edge deployment on embedded devices and mobile platforms.

A.3 Dataset Access

The PTB-XL dataset is publicly available via PhysioNet:

> Wagner, P., et al. (2020). *PTB-XL, a large publicly available electrocardiography dataset.* Scientific Data 7, 154.
> https://doi.org/10.13026/x4td-x982

A.4 Reproducibility

All experiments were conducted with a fixed random seed (`seed = 42`) for NumPy, Python, and PyTorch. The official PTB-XL fold assignments (folds 1–10) were used without modification to ensure comparability with published results.

A.5 Contact

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