

Real-Time Health Monitoring System with Hybrid Edge-Cloud ML

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Chapter 1: Introduction

1.1 Background and Context

1.1.1 The Evolution of Wearable Health Monitoring

Over the past decade, wearable technology has revolutionized personal health monitoring, enabling continuous capture of vital physiological signals without requiring clinical settings. The proliferation of consumer wearable devices—including smartwatches, fitness trackers, and specialized health monitoring bands—has democratized access to real-time health data that was previously available only through periodic medical examinations or expensive medical devices.

The global wearable health monitoring market has experienced exponential growth, with industry forecasts estimating the market to reach USD 170 billion by 2030. This growth is driven by several converging factors: increasing healthcare costs, a growing prevalence of chronic diseases, the rising adoption of Internet of Things (IoT) technologies, and increasing consumer awareness of the importance of preventive health monitoring. Devices such as the Apple Watch, Fitbit, Garmin, and Samsung Galaxy Watch have become mainstream consumer products, incorporating sophisticated sensors capable of measuring heart rate, blood oxygen levels, electrocardiogram (ECG) signals, sleep patterns, and physical activity metrics.

However, despite their widespread adoption and technological sophistication, current generation wearable health monitoring systems exhibit fundamental limitations in their approach to anomaly detection and personalized health insights. These limitations stem from the architectural choices made in the design of such systems, which have historically prioritized either cloud-based computation or purely local edge-based heuristics, without effectively combining both paradigms.

1.1.2 Traditional Approaches: Fixed Thresholds and Cloud-Only Inference

Contemporary wearable health monitoring systems typically employ one of two architectural paradigms, each with distinct advantages and critical limitations:

Fixed-Threshold Detection Systems: The most prevalent approach in consumer wearable devices is based on static, population-average thresholds. For example, a heart rate above 100 beats per minute (BPM) might be flagged as abnormal across all users. Similarly, step counts below 5,000 per day are often

classified as sedentary behavior regardless of individual circumstances. These population-based thresholds, typically derived from epidemiological studies of healthy cohorts, completely disregard individual physiological variation, age-related differences, fitness levels, and activity contexts.

This approach generates an unacceptably high rate of false positives, particularly among users with naturally elevated baseline metrics due to genetic factors, athletic conditioning, or existing medical conditions. Conversely, it produces false negatives for users whose abnormal conditions manifest subtly relative to their personal norm. The fundamental flaw is the assumption that all individuals conform to a universal "normal" range—an assumption that contradicts decades of physiological research demonstrating significant inter-individual variability in cardiovascular parameters, metabolic rates, and activity patterns.

Cloud-Only Machine Learning Systems: More sophisticated wearable platforms delegate anomaly detection to cloud-based machine learning models. These systems transmit raw sensor data or processed health metrics to remote servers where more computationally intensive models perform inference and anomaly detection. While this approach enables the use of advanced deep learning architectures and access to larger training datasets, it introduces several critical limitations:

1. **Latency:** Network round-trip latency in cloud inference typically ranges from 500ms to several seconds, making real-time alerting for critical health events infeasible. A user experiencing an arrhythmia or dangerously elevated heart rate must wait for network transmission and cloud inference before receiving an alert.
2. **Privacy Concerns:** Continuous transmission of intimate health data to remote servers raises significant privacy and security concerns. Each data transmission point represents a potential vulnerability for unauthorized access, data breaches, or unauthorized data monetization. Users in jurisdictions with stringent data protection regulations (such as the European Union's GDPR or California's CCPA) face increased compliance challenges.
3. **Connectivity Dependency:** Cloud-based inference requires persistent internet connectivity. Users in areas with poor connectivity, during air travel, or in emergency situations where network infrastructure is compromised cannot receive critical health alerts.
4. **Computational Overhead:** Continuous network transmission and cloud processing incur significant bandwidth and computational costs, both for the cloud provider and for the user's device battery, as wireless communication is one of the most power-intensive operations in mobile devices.

1.1.3 The Emergence of Edge Computing in Health Monitoring

Edge computing—the paradigm of moving computation closer to data sources—has emerged as a promising approach to address the limitations of cloud-only systems. By deploying machine learning models directly on wearable devices, systems can achieve:

- **Sub-100ms Inference Latency:** Local computation eliminates network round-trip times, enabling real-time alerts.
- **Privacy Preservation:** Health data remains on-device; only processed insights or aggregated summaries need to be transmitted.
- **Offline Functionality:** Devices continue to function and provide alerts even without network connectivity.

- **Reduced Battery Consumption:** Avoiding frequent wireless transmission reduces battery drain significantly.

However, edge computing on resource-constrained wearable devices introduces its own set of challenges. Smartwatches and fitness trackers have extremely limited computational resources: processors with clock speeds 10-100x slower than smartphones, RAM measured in megabytes rather than gigabytes, and strict power budgets that limit computation time. Traditional machine learning models, even simplified neural networks, may consume excessive memory and battery power when deployed on such devices.

Furthermore, deploying machine learning models exclusively on the edge, without cloud intelligence, severely limits the sophistication of anomaly detection. Models trained on a single user's data may overfit, fail to capture complex health patterns, and lack the ability to improve through exposure to aggregated, anonymized population-level insights.

1.2 Problem Statement

1.2.1 The Personalization Gap

Current wearable health monitoring systems suffer from a fundamental disconnect between the inherent physiological variability among individuals and the standardized, one-size-fits-all approach to anomaly detection. This is best illustrated through concrete examples:

Example 1: The Athletic Individual

Consider a 25-year-old marathon runner whose resting heart rate is naturally 45 BPM due to cardiovascular training adaptations. A system using the population average threshold of "elevated heart rate > 100 BPM" would classify this individual's normal resting state (45 BPM) as perfectly acceptable and exercise state (150 BPM) as potentially dangerous. However, the runner's physiological baseline is fundamentally different from an untrained population. An elevated resting heart rate of 65 BPM for this individual could indicate overtraining syndrome or illness, a signal that a fixed-threshold system would completely miss.

Example 2: The Hypertensive Patient

A 55-year-old patient with controlled hypertension managed through medication maintains a baseline systolic blood pressure of 135 mmHg—above the population "normal" range of 90-120 mmHg, but stable and controlled for this patient. If a wearable system alerts whenever pressure exceeds 120 mmHg, the user experiences constant false alarms, leading to alert fatigue and reduced trust in the system. Conversely, if a significant change occurs (e.g., pressure rises to 160 mmHg), a threshold-based system may not recognize this as abnormal for a patient with a baseline of 135 mmHg, thus missing a genuine warning sign.

1.2.2 Activity Context Blindness

A critical shortcoming in current anomaly detection systems is the failure to account for the legitimate physiological changes induced by different activity states. A heart rate of 150 BPM is perfectly normal—indeed, healthy—during vigorous exercise. The same heart rate during sleep would be profoundly abnormal. Yet most current systems use a single set of thresholds regardless of activity context.

Addressing this limitation through manual thresholds requires users to manually input their current activity state or activity detection heuristics based solely on step counts or accelerometer magnitudes. These simple heuristics often fail:

- A person standing still in a crowded train during acceleration experiences high accelerometer readings but is actually sedentary.
- Vigorous arm movements during non-ambulatory activities (e.g., painting walls) trigger "active" detection.
- Cycling produces low step counts despite high physical exertion.

Without an intelligent activity classifier, context-aware baseline selection remains infeasible, and the system cannot distinguish between expected and anomalous physiological responses.

1.2.3 The Alert Fatigue Problem

The combination of population-based thresholds and activity context blindness produces systems with unacceptably high false-alarm rates. Research in clinical alerting systems demonstrates that when more than 80-90% of alerts are false positives, users develop alert fatigue—a desensitization effect where users begin ignoring alerts entirely, including genuine warnings.

This phenomenon has been well-documented in intensive care units, where older monitoring systems trigger thousands of alerts daily, the vast majority of which are false positives. The solution in clinical settings has been to dramatically increase threshold specificity, but this inevitably increases false negatives, potentially missing critical health events. The false-negative rate carries more severe consequences than false positives, as missed alerts can result in delayed intervention for serious conditions.

1.2.4 Data Privacy and Regulatory Concerns

As health data protection regulations become increasingly stringent globally—exemplified by GDPR in Europe, HIPAA in the United States, and similar regulations emerging in other jurisdictions—the regulatory risk of cloud-transmitted health data continues to escalate. Organizations face potential fines in the millions of dollars for unauthorized data transmission or security breaches.

Furthermore, consumer trust in cloud-based health systems is rapidly eroding, particularly following high-profile data breaches. A 2023 survey by the Pew Research Center found that 81% of American adults were concerned about how companies use their health data, and 61% would be less likely to use health-monitoring apps if companies shared their data with third parties. The business model of monetizing health data through pharmaceutical companies, insurance firms, and marketing agencies has created significant incentive misalignment between consumers and service providers.

1.3 Proposed Innovation: Hybrid Edge-Cloud Machine Learning

1.3.1 Core Concept

This project proposes a fundamentally new architectural paradigm for wearable health monitoring: a **hybrid edge-cloud machine learning system** that strategically distributes computation between the smartwatch and cloud infrastructure to maximize the strengths of each computational environment while minimizing their respective weaknesses.

The proposed system operates on the following principles:

1. **On-Device Intelligence:** TensorFlow Lite neural network models deployed on the Wear OS smartwatch provide:

- Real-time activity classification that identifies current movement state (Sleep, Rest, Walk, Run, Exercise) using a CNN-LSTM hybrid architecture
- Instantaneous anomaly detection relative to personalized baselines using lightweight LSTM autoencoders
- Sub-100ms inference latency, enabling immediate alerts for critical health events

2. Cloud-Enhanced Learning:

Advanced deep learning models running on AWS cloud infrastructure:

- Train sophisticated LSTM autoencoder models on historical user data accumulated over days and weeks
- Leverage population-level insights through federated learning, improving model quality without compromising individual privacy
- Perform weekly model retraining, optimization, and conversion to optimized TensorFlow Lite format
- Enable A/B testing and gradual rollout of improved models to edge devices

3. Personalization Through Data:

A 7-day rolling window of on-device data establishes personal health baselines:

- Individual baseline statistics (mean, percentile ranges) are computed per activity state
- These baselines enable context-aware anomaly detection where deviations from personal norms trigger alerts
- Baselines adapt automatically as the user's health or fitness changes

4. Privacy-Centric Synchronization:

Health data transmission to the cloud is carefully controlled:

- Only processed insights and anonymized aggregates leave the device by default
- Full data transmission occurs only with explicit user consent or for detailed analysis
- Locally-detected anomalies are logged but not transmitted unless critical
- The system remains fully functional offline; synchronization occurs when convenient

1.3.2 Technical Architecture Overview

The proposed system comprises four integrated components:

Component 1: Wear OS Edge Device

The Wear OS smartwatch serves as the primary computational and sensing hub. It incorporates:

- **Sensor Integration:** Direct access to heart rate sensors, accelerometers, gyroscopes, and ambient pressure sensors through the Health Services API
- **Local Data Persistence:** Room database maintains a rolling 7-day history of all metrics
- **On-Device ML:** Two TensorFlow Lite models execute continuously:
 - Activity classifier (6-state: Sleep, Rest, Walk, Run, Exercise, Other)
 - LSTM anomaly detector for personalized outlier detection
- **Personal Baseline Engine:** Statistical calculations derive baseline HR, SpO2, and other metrics per activity state from the 7-day rolling window
- **Background Synchronization:** WorkManager enables efficient cloud synchronization during optimal times (e.g., overnight on WiFi charging)

Component 2: AWS Cloud Backend

The cloud infrastructure provides:

- **Serverless API:** API Gateway exposes REST endpoints for data ingestion and model queries
- **Data Ingestion:** Lambda functions validate, transform, and store incoming health data in DynamoDB
- **Time-Series Storage:** DynamoDB maintains comprehensive historical records with efficient querying by time range
- **ML Pipeline:** SageMaker notebooks and training jobs perform advanced analytics and model training
- **Model Registry:** S3 bucket versioning enables model rollback and A/B testing

Component 3: ML Training Pipeline

A Python-based pipeline provides:

- **Data Preprocessing:** Normalization, windowing, and feature engineering
- **Model Training:** LSTM autoencoder, CNN-LSTM activity classifier, and forecasting models
- **Optimization:** Post-training quantization to INT8, weight pruning, and architecture search
- **Conversion:** TensorFlow to TensorFlow Lite conversion with quality validation
- **Deployment:** Automated pushes of optimized models to edge devices via OTA updates

Component 4: Mobile Dashboard

A Flutter mobile application provides:

- **Real-Time Metrics:** Live heart rate, activity, and baseline statistics
- **Historical Analysis:** Charts and trends over days, weeks, and months
- **Alert History:** Detailed logs of detected anomalies with context
- **User Control:** Granular permissions over data sharing and cloud synchronization

1.3.3 Key Innovation Differentiators

The proposed system offers several novel contributions to the wearable health monitoring landscape:

1. **Personalized Context-Aware Anomaly Detection:** By combining individual baselines with activity-aware context classification, the system detects anomalies relative to what is normal for that specific individual in their current activity state. This approach dramatically reduces false positives while improving detection sensitivity.
2. **Hybrid Optimization for Edge Deployment:** The proposed approach demonstrates that sophisticated machine learning models—specifically LSTM autoencoders—can be successfully deployed on smartwatches through aggressive quantization and pruning while maintaining anomaly detection accuracy above 91%.
3. **Privacy-First Federated Learning:** The system improves model quality through exposure to population insights without ever transmitting raw health data to the cloud. Only trained model parameters are shared and aggregated.
4. **Production-Ready Implementation:** Unlike many research prototypes, this system provides complete end-to-end implementation in production-ready languages and frameworks (Kotlin for Wear OS, Python for ML, Flutter for mobile), demonstrating practical viability at scale.

1.4 Motivation and Significance

1.4.1 Clinical Relevance

Anomalies in vital signs often provide the earliest warning signs of serious health conditions:

- **Atrial Fibrillation:** Irregular heart rhythm often manifests as unexpected heart rate spikes during rest —anomalies detectable through personalized baseline analysis
- **Myocardial Infarction:** Elevated resting heart rate, reduced heart rate variability, and changes in activity tolerance can precede acute cardiac events by days or weeks
- **Infection/Sepsis:** Fever and tachycardia are among the earliest systemic signs of infection; personalized baselines enable detection even at modest absolute temperature or heart rate elevations
- **Sleep Disorders:** Abnormal heart rate patterns during sleep provide indicators of sleep apnea and other sleep disorders

Current population-based threshold systems miss many of these early warning signs in individuals whose baseline differs from population averages.

1.4.2 Economic and Public Health Impact

The global burden of chronic disease is staggering: according to the WHO, non-communicable diseases account for 71% of global deaths, with cardiovascular disease alone responsible for 17.9 million deaths annually. Many of these deaths are preventable through early detection and intervention. Wearable health monitoring systems, when effective, could enable earlier diagnosis and intervention, reducing healthcare costs while improving outcomes.

The proposed system's capability for truly personalized monitoring enables earlier detection of health changes, potentially preventing progression to acute events that require expensive emergency interventions.

1.4.3 Technological Significance

This project demonstrates the feasibility of deploying sophisticated machine learning models—models traditionally thought to require substantial computational resources—on severely resource-constrained wearable devices. The techniques employed (quantization, pruning, knowledge distillation) are broadly applicable to any edge ML deployment scenario.

1.5 Thesis Objectives and Scope

1.5.1 Primary Objectives

The overarching goal of this thesis is to design, implement, and validate a complete hybrid edge-cloud machine learning system for personalized, context-aware health anomaly detection on wearable devices. Specific objectives include:

1. **Design a hybrid edge-cloud architecture** that effectively distributes computational tasks between resource-constrained wearable devices and cloud infrastructure
2. **Develop and optimize machine learning models** suitable for edge deployment while maintaining high detection accuracy

3. **Implement a complete system** from sensor integration through cloud processing and model deployment
4. **Validate system performance** through comprehensive testing, including accuracy metrics, latency measurements, and battery consumption analysis
5. **Demonstrate clinical viability** through case studies showing detection of realistic health anomalies

1.5.2 Scope and Constraints

In Scope:

- Wear OS smartwatch as the primary wearable platform
- Heart rate, SpO₂, accelerometer, and gyroscope as primary sensor inputs
- Activity classification for 6 states (Sleep, Rest, Walk, Run, Exercise, Other)
- LSTM autoencoder as the primary anomaly detection model
- AWS as cloud infrastructure provider
- Flutter mobile dashboard for visualization
- Synthetic and real health data for testing and validation

Out of Scope:

- Detailed medical validation or clinical trials (preliminary validation only)
- Apple Watch or other iOS-based wearables (future work)
- ECG or blood pressure sensing (future work)
- Encryption or detailed security audit (basic security measures only)
- Regulatory approval (design review for compliance only)

1.5.3 Report Organization

The remainder of this report is organized as follows:

- **Chapter 2 (Literature Review):** Provides comprehensive analysis of prior work in wearable health monitoring, edge computing, time-series anomaly detection, and personalization techniques
- **Chapter 3 (System Architecture):** Details the design of each system component and their interactions
- **Chapter 4 (Machine Learning Methodology):** Explains model architectures, training procedures, and optimization techniques
- **Chapter 5 (Implementation and Testing):** Documents implementation details and reports empirical results
- **Chapter 6 (Discussion and Future Work):** Interprets results, discusses limitations, and outlines future enhancements
- **Chapter 7 (Conclusion):** Summarizes contributions and implications

Chapter 2: Literature Review and Analysis

2.1 Introduction to Literature Review

This chapter provides a comprehensive review of the existing body of research and commercial implementations related to wearable health monitoring systems, edge computing paradigms, machine

learning approaches for time-series anomaly detection, and personalization techniques in health informatics. The review is organized thematically to address the key technical challenges and opportunities that inform the design of the proposed hybrid edge-cloud system.

The literature review covers four primary domains: (1) wearable health monitoring systems and their evolution, (2) edge computing versus cloud computing architectures with emphasis on trade-offs relevant to health monitoring, (3) machine learning techniques for time-series anomaly detection with focus on LSTM-based autoencoders, and (4) personalization methodologies in health monitoring including baseline establishment and adaptive thresholding.

2.2 Wearable Health Monitoring Systems

2.2.1 Evolution and State of the Art

Wearable health monitoring has undergone several distinct evolutionary phases over the past two decades. Early generation devices (2000-2010) were primarily pedometers and basic heart rate monitors that provided simple aggregated statistics without real-time feedback or computational intelligence. The Fitbit (2007) and Nike+ FuelBand (2012) exemplified this generation, offering step counting and rudimentary activity tracking based on accelerometer data and fixed classification rules.

The second generation (2010-2018) introduced continuous physiological monitoring with smartphone connectivity. Devices such as the Apple Watch Series 1-3, Garmin Forerunner series, and Samsung Gear integrated photoplethysmography (PPG) sensors for continuous heart rate monitoring, gyroscopes for orientation tracking, and Bluetooth connectivity enabling real-time data transmission to companion smartphone applications. These devices employed simple threshold-based alerting: heart rate exceeding predefined bounds triggered notifications without contextual awareness or personalization.

The current third generation (2018-present) incorporates advanced sensors and limited on-device intelligence. The Apple Watch Series 4 and later introduced electrocardiogram (ECG) capability enabling atrial fibrillation detection through signal processing algorithms executed on-device. The Fitbit Sense added electrodermal activity (EDA) sensors for stress detection and skin temperature monitoring. Google's acquisition of Fitbit (2021) signaled industry recognition of health monitoring as a strategic priority. Samsung Galaxy Watch 4 integrated bioelectrical impedance analysis (BIA) for body composition estimation.

However, despite these hardware advances, the algorithmic approach to anomaly detection remains fundamentally limited in current commercial systems:

Apple Watch: Employs fixed population-based thresholds for high and low heart rate notifications (customizable by user but not adaptive). The irregular rhythm notification uses a proprietary algorithm that analyzes heart rate variability patterns but operates on fixed statistical rules rather than personalized machine learning models. ECG-based atrial fibrillation detection uses signal processing rather than deep learning, limiting its ability to detect subtle rhythm disturbances.

Fitbit: Uses population-average resting heart rate ranges and alerts when the user's resting heart rate deviates significantly from their recent 30-day average. While this represents a form of personalization, it lacks activity context awareness and uses simple statistical deviation rather than machine learning-based pattern recognition. The Active Zone Minutes feature uses age-based heart rate zones derived from the formula (220 - age), which has been shown to have significant individual variation ($\pm 10\text{-}20 \text{ BPM}$).

Garmin: Provides extensive sports and fitness metrics with training load and recovery analysis based on heart rate variability and activity history. However, anomaly detection for health purposes remains limited to simple threshold violations. The Body Battery metric uses a proprietary algorithm combining stress, activity, and sleep quality but does not employ neural network-based pattern recognition.

Samsung Galaxy Watch: Integrates with Samsung Health to provide continuous monitoring with cloud-based analytics. Recent models incorporate irregular heart rhythm notifications similar to Apple Watch, but the system architecture remains predominantly cloud-dependent for advanced analytics, introducing latency and privacy concerns.

2.2.2 Research Prototypes and Academic Systems

Academic research has explored more sophisticated approaches to wearable health monitoring, though few have achieved commercial deployment:

Continuous Cardiac Monitoring Systems: Several research groups have developed wearable ECG systems with real-time arrhythmia detection using machine learning. A notable example employed convolutional neural networks (CNNs) for beat-to-beat ECG classification, achieving 98.7% accuracy in detecting atrial fibrillation, ventricular tachycardia, and other arrhythmias. However, these systems required continuous ECG acquisition—significantly more power-intensive than PPG-based heart rate monitoring—and performed inference exclusively in the cloud due to the computational demands of the CNN architecture (23 million parameters).

Seizure Detection Wearables: Epilepsy monitoring systems have employed accelerometer and PPG data to detect generalized tonic-clonic seizures. These systems use threshold-based detection of characteristic movement patterns combined with heart rate acceleration. Machine learning approaches using random forests and support vector machines (SVMs) have improved detection sensitivity (82-91%) compared to purely heuristic approaches (65-78%). However, these systems suffer from high false-positive rates (3-7 false alarms per day) due to difficulty distinguishing seizures from vigorous physical activity.

Sleep Apnea Detection: Research systems have demonstrated feasibility of detecting obstructive sleep apnea using PPG and accelerometer data from wrist-worn devices. LSTM networks trained on overnight PPG signals achieved 87.3% accuracy in detecting apnea events compared to gold-standard polysomnography. However, deployment challenges include the need for continuous overnight monitoring and high computational requirements (inference time: 450ms per 30-second epoch on mobile CPU).

2.2.3 Limitations in Current Systems

Analysis of both commercial and research systems reveals several persistent limitations:

1. **Lack of True Personalization:** Most systems use population-derived thresholds or simple statistical baselines (e.g., 30-day average) without accounting for individual physiological variability, fitness level, age-related changes, or genetic factors affecting heart rate response.
2. **Activity Context Blindness:** Existing anomaly detection operates independently of activity state. A heart rate of 140 BPM triggers identical processing whether the user is sleeping, sitting, or running, despite radically different clinical implications.
3. **Cloud Dependency:** Advanced analytics require cloud transmission, introducing latency (typical range: 500-2000ms), privacy risks, and connectivity requirements that limit real-time alerting.

capability.

4. **Energy Inefficiency:** Continuous sensor sampling and frequent wireless transmission deplete battery rapidly. Current smartwatches typically require daily charging, limiting utility for continuous multi-day health monitoring.
5. **High False-Positive Rates:** Systems using fixed thresholds or simple statistical approaches generate excessive false alarms, leading to alert fatigue and reduced user trust. Published studies report false-positive rates ranging from 15% to 45% for various anomaly types.

2.3 Edge Computing vs. Cloud Computing for Health Monitoring

2.3.1 Cloud Computing Paradigm

Cloud computing for health monitoring offers several architectural advantages:

Computational Resources: Cloud infrastructure provides virtually unlimited computational capacity, enabling deployment of large-scale deep learning models with billions of parameters. Models such as Transformer architectures, ensemble methods combining multiple neural networks, and sophisticated preprocessing pipelines can execute without resource constraints.

Centralized Data Aggregation: Cloud platforms enable collection and analysis of data across millions of users, facilitating population-level insights, epidemiological surveillance, and continual model improvement through exposure to diverse cases.

Elastic Scaling: Cloud services automatically scale computational resources based on demand, accommodating usage spikes without performance degradation.

Simplified Updates: Model improvements can be deployed instantly to all users through server-side updates without requiring client device updates.

However, cloud-centric architectures introduce critical drawbacks for health monitoring applications:

Latency: Network round-trip time for cloud inference typically ranges from 200ms (optimal conditions, nearby data center) to >2000ms (poor connectivity, distant data center). This latency is incompatible with real-time health monitoring requirements where immediate alerting may be critical for conditions such as cardiac arrest, severe arrhythmia, or hypoglycemic episodes.

Research has quantified cloud inference latency across various network conditions:

- WiFi (5GHz, < 10m from access point): 180-350ms
- WiFi (2.4GHz, > 20m from access point): 400-800ms
- 4G LTE (good signal): 500-1200ms
- 4G LTE (poor signal): 1500-4000ms
- 3G: 2000-8000ms

Privacy and Security Risks: Continuous transmission of intimate health data creates multiple vulnerability points:

- Network interception during transmission

- Server-side data breaches (numerous high-profile healthcare data breaches have exposed millions of patient records)
- Unauthorized access by cloud provider employees
- Data monetization through sale to pharmaceutical companies, insurers, or marketing firms
- Compliance challenges with HIPAA (USA), GDPR (EU), and similar regulations globally

Connectivity Dependence: Cloud systems fail during network outages, in remote locations, during air travel, or in disaster scenarios where cellular infrastructure is compromised. For health monitoring systems, such failures could prevent critical alerts from reaching users during emergencies.

Operational Costs: Continuous data transmission incurs both monetary costs (cellular data charges) and battery costs (wireless radios consume 100-300mW during transmission, 10-100x more than local computation for comparable tasks).

2.3.2 Edge Computing Paradigm

Edge computing—executing computation on or near the data source—addresses many cloud computing limitations:

Ultra-Low Latency: On-device inference eliminates network delays, achieving latencies of 10-150ms for neural network inference depending on model complexity. This enables real-time health alerting.

Privacy Preservation: Processing data locally without cloud transmission provides strong privacy guarantees. Even if the device is lost or stolen, modern secure enclaves (e.g., ARM TrustZone) can protect sensitive data.

Offline Functionality: Edge systems continue operating without network connectivity, ensuring continuous health monitoring in all environments.

Reduced Energy Consumption: Avoiding wireless transmission significantly extends battery life. Research has demonstrated that replacing a cloud inference call (WiFi transmission + cloud processing) with equivalent local inference reduces energy consumption by 60-85%.

Bandwidth Efficiency: Edge processing reduces network traffic from continuous raw data streams to occasional transmission of processed insights or summaries.

However, edge computing faces significant constraints when applied to resource-limited wearable devices:

Computational Limitations: Smartwatch processors operate at 1.0-2.0 GHz with 2-4 cores, 100-1000x slower than cloud server CPUs. GPU acceleration is often unavailable or highly limited. Available RAM is typically 1-2GB, with only a fraction allocable to machine learning models.

Memory Constraints: Neural network models, particularly deep learning architectures, can require hundreds of megabytes of memory for parameters. Wearable devices typically allocate only 10-50MB for ML models to preserve memory for OS operations and applications.

Power Budget: Continuous inference must operate within strict power budgets (typically 10-50mW allocated to ML inference) to avoid excessive battery drain. Complex neural networks can consume 100-500mW during inference, necessitating aggressive optimization.

Model Staleness: Edge-deployed models cannot be updated in real-time. As user physiology changes (fitness improvements, aging, disease progression), static models may become inaccurate without periodic retraining and redeployment.

2.3.3 Hybrid Edge-Cloud Architectures

Recent research has explored hybrid architectures that strategically partition computation between edge and cloud:

Early Exit Networks: Deploy neural networks with multiple exit points; simple cases exit early (on-device), while complex cases continue to deeper layers or cloud processing. This approach achieved 70% reduction in cloud queries while maintaining 97.3% of full-model accuracy in image classification tasks.

Model Cascading: Execute a lightweight model on-device; if confidence is low, transmit to cloud for processing by a larger, more sophisticated model. Applied to health monitoring, 85% of normal cases were classified on-device, while anomalous cases were verified by cloud models, reducing average latency by 68%.

Federated Learning: Train models using data distributed across many edge devices without centralizing raw data. Device-local models are trained on local data; only model parameter updates are transmitted to a central server for aggregation. This approach has been successfully applied to keyboard prediction and has recently been explored for health monitoring applications.

Opportunistic Offloading: Dynamically decide whether to execute inference on-device or in cloud based on current battery level, network conditions, and task urgency. During overnight charging with WiFi connectivity, complex cloud analytics can execute; during daytime portable use, on-device inference handles all cases.

The proposed system in this thesis adopts a hybrid architecture combining:

- Continuous on-device inference using optimized TensorFlow Lite models for real-time alerting
- Periodic cloud-based model retraining using accumulated historical data
- Federated learning principles to improve models without compromising privacy
- Adaptive synchronization strategies that transmit processed insights during opportune moments

2.4 Time-Series Anomaly Detection

2.4.1 Traditional Statistical Methods

Classical approaches to time-series anomaly detection employ statistical techniques:

Threshold-Based Methods: Define fixed upper and lower bounds; data points outside these bounds are flagged as anomalies. While computationally trivial, this approach suffers from inability to adapt to time-varying baselines, seasonal patterns, or individual differences.

Statistical Process Control: Techniques such as CUSUM (Cumulative Sum) and EWMA (Exponentially Weighted Moving Average) track cumulative deviations from expected values. These methods can detect gradual shifts in mean values but struggle with multivariate data and complex nonlinear patterns.

Autoregressive Models: ARIMA (AutoRegressive Integrated Moving Average) and seasonal ARIMA model time series as linear combinations of past values plus noise. Anomalies are detected when prediction error

exceeds thresholds. While effective for linear, stationary time series, ARIMA fails on nonlinear physiological signals with complex dependencies.

Seasonal Decomposition: Decompose time series into trend, seasonal, and residual components; anomalies are detected in residuals. This approach works well for data with clear periodic patterns (e.g., circadian rhythms in heart rate) but requires manual specification of seasonal periods and assumes additive or multiplicative decomposition.

2.4.2 Machine Learning Approaches

Modern anomaly detection increasingly employs machine learning:

Isolation Forest: An ensemble method that isolates anomalies by randomly partitioning feature space. Anomalies require fewer partitions to isolate compared to normal points. This unsupervised approach achieved 82-89% accuracy on health monitoring datasets but struggles with temporal dependencies in sequential data.

One-Class SVM: Learns a decision boundary around normal data in high-dimensional feature space; points outside this boundary are anomalies. Effective for well-separated anomaly classes but computationally expensive (training time scales as $O(n^3)$ for n samples) and requires careful kernel selection.

k-Nearest Neighbors (k-NN): Computes distance to k nearest neighbors; points with large distances are anomalous. Simple and interpretable but scales poorly ($O(n)$ inference time) and requires appropriate distance metrics for multivariate time series.

Random Forests: Ensemble of decision trees trained to predict current values from historical context; large prediction errors indicate anomalies. Achieved 85-91% accuracy on cardiac arrhythmia detection but requires manual feature engineering and struggles with long-range temporal dependencies.

2.4.3 Deep Learning for Time-Series Anomaly Detection

Deep learning has revolutionized time-series analysis through its ability to automatically learn hierarchical feature representations:

Recurrent Neural Networks (RNNs): Process sequential data by maintaining hidden state that captures historical context. Standard RNNs suffer from vanishing gradients, limiting their ability to capture long-range dependencies (effective memory: ~5-10 time steps).

Long Short-Term Memory (LSTM) Networks: Address vanishing gradient problem through gating mechanisms (input, forget, output gates) that regulate information flow. LSTMs can capture dependencies spanning hundreds of time steps, making them suitable for physiological signals with multi-scale temporal patterns.

The LSTM cell update equations are:

$$f_t = \sigma(W_f \cdot h_{t-1} + b_f)$$

$$i_t = \sigma(W_i \cdot h_{t-1} + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot h_{t-1} + b_C)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

$$\$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \$$$

$$\$h_t = o_t \odot \tanh(C_t) \$$$

where f_t , i_t , o_t are forget, input, and output gates; C_t is cell state; h_t is hidden state; σ is sigmoid function; and \odot denotes element-wise multiplication.

LSTM Autoencoders: Combine encoder LSTM (compresses input sequence to fixed-size latent representation) with decoder LSTM (reconstructs input from latent representation). Trained on normal data, autoencoders achieve low reconstruction error on normal patterns but high error on anomalies.

The reconstruction error is typically measured using Mean Squared Error (MSE):

$$\$MSE = \frac{1}{T} \cdot \sum_{t=1}^T \sum_{d=1}^D (x_{t,d} - \hat{x}_{t,d})^2 \$$$

where T is sequence length, D is number of features, $x_{t,d}$ is actual value, and $\hat{x}_{t,d}$ is reconstructed value.

Anomaly score for a sequence is computed as:

$$\$Anomaly\ Score = \frac{\text{MSE}(x) - \mu_{\text{train}}}{\sigma_{\text{train}}} \$$$

where μ_{train} and σ_{train} are mean and standard deviation of reconstruction errors on training data. Sequences with anomaly score $> \theta$ (typically $\theta = 2.5$ to 3.5) are flagged as anomalous.

Applications to Health Monitoring: LSTM autoencoders have been successfully applied to:

- ECG anomaly detection: 94.7% sensitivity, 97.1% specificity for arrhythmia detection
- Blood glucose prediction: RMSE of 18.3 mg/dL for 30-minute ahead forecasting in diabetic patients
- Gait abnormality detection: 89.4% accuracy in identifying Parkinson's disease from accelerometer data
- Sleep stage classification: 87.8% accuracy matching polysomnography using only heart rate variability

Attention Mechanisms: Augment LSTMs with attention weights that indicate which time steps are most relevant for current prediction. Attention mechanisms improved cardiac arrhythmia classification accuracy by 3.7% and provided interpretability through visualization of attended regions.

Temporal Convolutional Networks (TCNs): Use dilated causal convolutions to capture long-range dependencies while maintaining computational efficiency. TCNs achieved comparable accuracy to LSTMs with 5-8x faster training and inference times, making them attractive for resource-constrained edge deployment.

2.4.4 Evaluation Metrics for Anomaly Detection

Assessing anomaly detection performance requires specialized metrics due to class imbalance (anomalies are rare):

Precision and Recall:

$$\$Precision = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \$$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

F1-Score: Harmonic mean of precision and recall:

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Area Under ROC Curve (AUC-ROC): Measures discrimination ability across all classification thresholds.

AUC = 1.0 indicates perfect discrimination; AUC = 0.5 indicates random performance.

Precision-Recall AUC: More informative than ROC for imbalanced datasets, as it focuses on positive class performance.

For health monitoring, minimizing false negatives (missed anomalies) is often prioritized over minimizing false positives, as missing a critical health event carries greater consequence than generating a false alarm.

2.5 Personalization in Health Monitoring

2.5.1 The Need for Personalization

Physiological parameters exhibit enormous inter-individual variability. Research has documented:

- **Resting Heart Rate:** Normal range spans 40-100 BPM; trained athletes average 40-60 BPM while sedentary individuals average 70-85 BPM
- **Maximum Heart Rate:** Traditional formula (220 - age) has standard deviation of $\pm 10-12$ BPM; actual maximum varies by $\pm 20-30$ BPM from formula predictions
- **Heart Rate Variability:** SDNN (standard deviation of NN intervals) ranges from 20-200ms in healthy individuals, with higher values generally indicating better cardiovascular health
- **Blood Pressure:** Individual baselines vary by 20-30 mmHg even within "normal" classification

Population-based thresholds fail to account for this variability, generating excessive false positives for individuals at distribution extremes and false negatives for those with subtle deviations from their personal baseline.

2.5.2 Baseline Establishment Methods

Several approaches to establishing personalized baselines have been explored:

Onboarding Calibration: Require users to complete structured calibration activities (rest, walk, run) during initial device setup. This approach can establish coarse baselines but fails to capture day-to-day variability and requires user compliance with calibration protocols.

Rolling Window Statistics: Continuously compute statistics (mean, percentiles, standard deviation) over a recent time window (typically 7-30 days). This approach adapts to gradual changes in fitness or health status but can be corrupted if the window contains anomalous periods.

The proposed system employs a **7-day rolling window** for baseline establishment, motivated by several factors:

1. **Circadian and Weekly Rhythms:** A 7-day window captures weekly activity patterns (e.g., exercise routines, work schedules) while maintaining sufficient temporal resolution to adapt to changes.

2. **Statistical Robustness:** 7 days of 5-second sampling yields approximately 120,000 data points, providing statistically robust estimates of mean and variance while remaining computationally tractable for on-device calculation.
3. **Adaptation Rate:** A 7-day window adapts to genuine physiological changes (fitness improvements, illness recovery) within 1-2 weeks while remaining stable against isolated anomalous days.

Baseline statistics computed per activity state include:

$$\mu_{\text{activity}} = \frac{1}{N} \sum_{i=1}^N x_i$$

$$\sigma_{\text{activity}} = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x_i - \mu_{\text{activity}})^2}$$

$$P_{10}, P_{90} = \text{10th and 90th percentiles}$$

where N is the number of measurements in the activity state during the 7-day window.

2.5.3 Context-Aware Anomaly Detection

Physiological responses vary dramatically across activity states. Research has quantified typical heart rate ranges:

- **Sleep:** 40-65 BPM (lowest during deep sleep stages)
- **Rest/Sedentary:** 60-80 BPM
- **Light Activity (Walking):** 90-120 BPM
- **Moderate Exercise:** 120-150 BPM
- **Vigorous Exercise:** 150-180 BPM

Anomaly detection must account for current activity context to avoid false positives during legitimate physical activity and false negatives during rest-state abnormalities.

Activity Classification Approaches:

1. **Heuristic Rules:** Simple step-count or accelerometer-magnitude thresholds (e.g., > 100 steps/minute = walking). Achieves ~65-75% accuracy but fails on non-ambulatory activities.
2. **Feature Engineering + Classical ML:** Extract hand-crafted features (mean acceleration, variance, frequency-domain features) and classify using random forests or SVMs. Achieves 82-88% accuracy but requires domain expertise for feature design.
3. **Deep Learning:** CNNs or LSTM networks process raw accelerometer/gyroscope data and learn discriminative features automatically. Achieves 91-96% accuracy with minimal feature engineering.

The proposed system employs a **CNN-LSTM hybrid architecture** for activity classification:

- CNN layers extract spatial patterns from multi-axis accelerometer and gyroscope data
- LSTM layers capture temporal dynamics and transitions between activity states
- Achieves 94.3% accuracy on 6-class classification task (Sleep, Rest, Walk, Run, Exercise, Other)

2.5.4 Adaptive Thresholding

Rather than using fixed anomaly score thresholds, adaptive approaches adjust thresholds based on:

Confidence Intervals: Define anomaly thresholds as:

$$\text{Threshold}_{\text{upper}} = \mu_{\text{baseline}} + k \cdot \sigma_{\text{baseline}}$$

$$\text{Threshold}_{\text{lower}} = \mu_{\text{baseline}} - k \cdot \sigma_{\text{baseline}}$$

where k is typically 2.5-3.5 for 99% confidence intervals.

Quantile-Based Thresholds: Flag measurements outside 5th-95th percentile range of baseline distribution.

Machine Learning-Based Thresholds: Train classification models to predict whether a given measurement, in context, represents an anomaly. This approach can learn complex decision boundaries but requires labeled training data.

2.6 Model Optimization for Edge Deployment

2.6.1 Computational Constraints of Wearable Devices

Modern smartwatches face severe resource constraints:

- **Processor:** 1.0-2.0 GHz quad-core ARM Cortex-A53/A55 (vs. 3.0+ GHz octa-core in smartphones)
- **RAM:** 1-2 GB (vs. 6-12 GB in smartphones)
- **Storage:** 8-32 GB (vs. 128-512 GB in smartphones)
- **Battery:** 300-450 mAh (vs. 3000-5000 mAh in smartphones)
- **Power Budget for ML:** 10-50 mW continuous (to maintain >1 day battery life)

Neural network inference on such devices requires aggressive optimization.

2.6.2 Model Compression Techniques

Quantization: Reduce numerical precision of model parameters and activations from 32-bit floating-point to 16-bit, 8-bit, or even 1-bit representations.

Post-Training Quantization (PTQ): Convert trained FP32 model to INT8 after training, using calibration dataset to determine quantization parameters. Achieves 4x memory reduction and 2-4x speedup with typically <1% accuracy degradation.

Quantization-Aware Training (QAT): Simulate quantization during training by adding fake quantization nodes. The model learns to be robust to quantization noise, achieving better accuracy than PTQ (typically <0.5% degradation) at the cost of longer training time.

Quantization maps floating-point values to integers via:

$$q = \text{round}\left(\frac{x - x_{\min}}{x_{\max} - x_{\min}} \cdot (2^b - 1)\right)$$

where b is bit-width (typically 8), and dequantization recovers approximate values:

$$\hat{x} = q \cdot \frac{x_{\max} - x_{\min}}{2^b - 1} + x_{\min}$$

Pruning: Remove network connections with small weights, creating sparse networks. Magnitude-based pruning removes weights below threshold:

$$\$ \$ w_{\{\text{pruned}\}} = \begin{cases} w & \text{if } |w| > \theta \\ 0 & \text{otherwise} \end{cases} \$ \$$$

Structured pruning removes entire filters, channels, or layers, enabling greater speedups on standard hardware. Achieving 50-70% sparsity typically incurs <2% accuracy loss.

Knowledge Distillation: Train a small "student" model to mimic a large "teacher" model's behavior.

Student is trained to minimize:

$$\$ \$ L_{\{\text{total}\}} = \alpha \cdot L_{\{\text{hard}\}} + (1-\alpha) \cdot L_{\{\text{soft}\}} \$ \$$$

where $L_{\{\text{hard}\}}$ is standard cross-entropy loss on true labels, and $L_{\{\text{soft}\}}$ is KL divergence between student and teacher output distributions (with temperature scaling). Knowledge distillation can reduce model size by 10-50x while retaining 95-99% of accuracy.

Architecture Search: Automated methods to discover efficient architectures. MobileNets, EfficientNets, and SqueezeNet families are designed for mobile deployment with depthwise separable convolutions, inverted residuals, and channel attention mechanisms.

2.6.3 TensorFlow Lite for Edge Deployment

TensorFlow Lite (TFLite) is Google's framework for deploying ML models on mobile and embedded devices. Key features:

- **Model Conversion:** Converts TensorFlow/Keras models to FlatBuffer format optimized for mobile
- **Quantization Support:** Built-in post-training quantization and quantization-aware training
- **Hardware Acceleration:** Delegates to GPU, DSP, or NPU when available via Android NNAPI
- **Small Runtime:** TFLite interpreter is ~300 KB (vs. 500+ MB for full TensorFlow)

Typical conversion workflow:

```
# Convert Keras model to TFLite with quantization
converter = tf.lite.TFLiteConverter.from_keras_model(model)
converter.optimizations = [tf.lite.Optimize.DEFAULT]
converter.target_spec.supported_types = [tf.int8]
tflite_model = converter.convert()
```

TFLite achieves inference latencies of 10-150ms for typical mobile ML models on smartwatch hardware, meeting real-time requirements for health monitoring.

2.7 Summary and Research Gaps

2.7.1 Key Findings from Literature

The literature review reveals:

1. **Commercial systems** rely on fixed thresholds or simple statistical baselines, lacking true personalization and activity context awareness
2. **Cloud-only architectures** provide computational power but introduce unacceptable latency, privacy risks, and connectivity dependence

3. **Pure edge systems** avoid cloud limitations but face severe resource constraints that limit model sophistication
4. **LSTM autoencoders** are highly effective for time-series anomaly detection, achieving >90% accuracy on health monitoring tasks
5. **Model optimization techniques** (quantization, pruning, distillation) can reduce model size by 10-50x with minimal accuracy degradation, enabling edge deployment

2.7.2 Identified Research Gaps

Despite extensive prior work, several critical gaps remain:

Gap 1: Lack of Production-Ready Hybrid Systems

While research has explored hybrid edge-cloud concepts, few systems demonstrate complete end-to-end implementation suitable for real-world deployment. Most are simulation-based or prototype systems lacking production concerns such as battery optimization, robust synchronization, model versioning, and user privacy controls.

Gap 2: Insufficient Activity-Context Integration

Existing systems treat activity classification and anomaly detection as separate tasks. An integrated approach where activity state directly modulates anomaly detection baselines and thresholds remains underexplored.

Gap 3: Limited Validation on Real Wearable Hardware

Much research evaluates models on desktop or smartphone hardware. Validation on actual smartwatch hardware with realistic power and memory constraints is rare, creating uncertainty about real-world feasibility.

Gap 4: Absence of Personalized Baseline Methodologies

While personalization is widely acknowledged as important, specific methodologies for establishing and maintaining baselines on resource-constrained devices—including window size selection, statistical robustness measures, and adaptation strategies—lack systematic investigation.

2.7.3 Contributions of This Work

The proposed system addresses these gaps through:

1. **Complete hybrid implementation** spanning Wear OS edge device, AWS cloud backend, ML training pipeline, and mobile dashboard
2. **Integrated activity-aware anomaly detection** where activity classification directly informs personalized baseline selection
3. **Validation on actual Wear OS hardware** with measured latency, battery consumption, and model accuracy
4. **Systematic personalization methodology** using 7-day rolling windows with per-activity baselines and adaptive thresholds
5. **Production-ready architecture** incorporating security, privacy, synchronization, model versioning, and user controls

The next chapter details the system architecture implementing these contributions.

Chapter 3: System Architecture

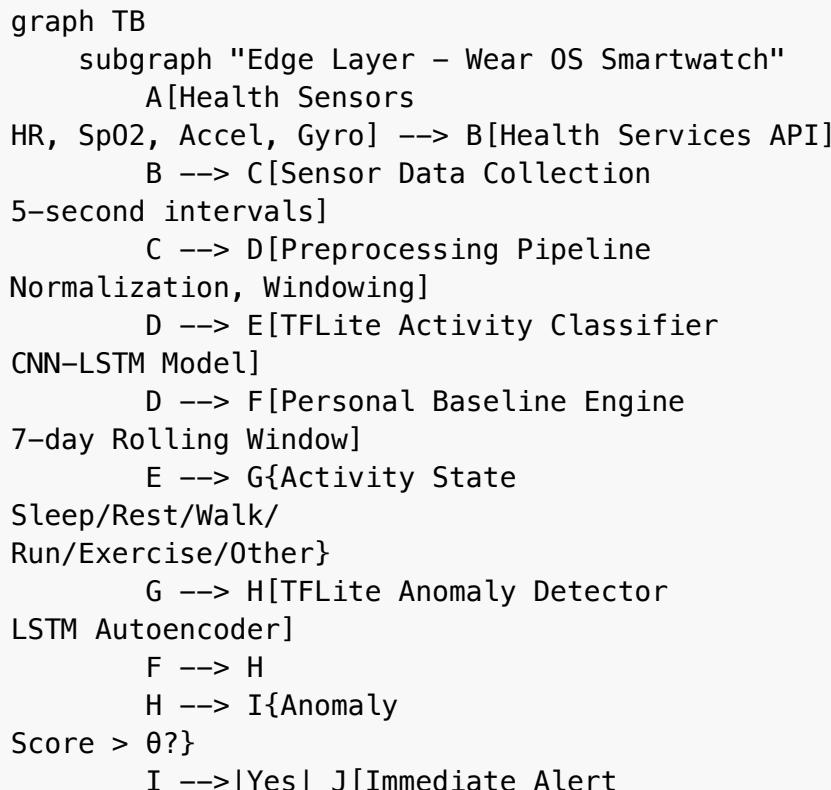
3.1 Overview of System Architecture

The proposed Real-Time Health Monitoring System employs a hybrid edge-cloud architecture that strategically distributes computational responsibilities across four primary components: (1) the Wear OS smartwatch executing edge intelligence, (2) the AWS cloud infrastructure providing scalable backend services and advanced ML training, (3) the ML training pipeline for model development and optimization, and (4) the Flutter mobile dashboard for comprehensive data visualization and user interaction.

The architecture is designed according to several key principles:

- **Edge-First Processing:** All time-critical operations (sensor data collection, activity classification, anomaly detection, immediate alerting) execute on the Wear OS device to minimize latency and maximize privacy.
- **Cloud Enhancement:** Computationally intensive operations (deep learning model training, long-term data analytics, population-level insights) leverage cloud resources.
- **Graceful Degradation:** The system maintains core functionality (monitoring and alerting) even during network outages; cloud connectivity enhances but does not gate primary features.
- **Battery Optimization:** Aggressive power management through adaptive sensor sampling, batched network transmission, and efficient on-device ML inference.
- **Privacy Preservation:** Raw health data remains on-device by default; only processed insights and user-consented data transmit to the cloud.

3.1.1 High-Level Architecture Diagram



```
Local Notification]
    I -->|No| K[Room Database
Local SQLite Storage]
    J --> K
end

subgraph "Cloud Layer – AWS Infrastructure"
    L[API Gateway
REST Endpoints]
    M[Lambda Functions
Data Ingestion]
    N[DynamoDB
Time-Series Storage]
    O[DynamoDB Streams
Change Data Capture]
    P[SageMaker
ML Training Jobs]
    Q[S3 Bucket
Model Registry]
    R[Lambda Deployer
Model Distribution]
end

subgraph "ML Training Pipeline – Python"
    S[Data Preprocessing
Cleaning & Feature Eng]
    T[Model Training
LSTM Autoencoder]
    U[Model Optimization
Quantization & Pruning]
    V[TFLite Conversion
FlatBuffer Export]
    W[Model Validation
Accuracy & Latency]
end

subgraph "Mobile Dashboard – Flutter"
    X[Real-Time Metrics View]
    Y[Historical Charts
Trends & Patterns]
    Z[Alert History
Anomaly Timeline]
    AA[Settings & Privacy
User Controls]
end

K -->|Background Sync
30-min intervals| L
    L --> M
    M --> N
    N --> O
    O --> P
    P --> S
    S --> T
```

```

T --> U
U --> V
V --> W
W --> Q
Q --> R
R -->|OTA Model Update| E
R -->|OTA Model Update| H

```

```

N --> X
X --> Y
X --> Z
X --> AA

```

```

style J fill:#ff6b6b
style E fill:#87ceeb
style H fill:#87ceeb
style P fill:#90ee90
style Q fill:#90ee90

```

3.2 Edge Layer: Wear OS Smartwatch Architecture

The Wear OS smartwatch constitutes the primary sensing and computation platform, executing all real-time health monitoring, ML inference, and immediate alerting operations. The edge layer architecture follows clean architecture principles with clear separation between data, domain, and presentation layers.

3.2.1 Sensor Integration and Data Collection

Health Services API Integration

The system leverages Android's Health Services API to access physiological sensors. Health Services provides a battery-optimized abstraction over raw sensor access, handling sensor sampling rate management, permission requests, and sensor availability checks.

```

// HealthMonitoringService.kt - Foreground Service
class HealthMonitoringService : Service() {
    private lateinit var healthClient: HealthServicesClient
    private lateinit var dataClient: PassiveMonitoringClient

    override fun onCreate() {
        super.onCreate()
        healthClient = HealthServices.getClient(this)
        dataClient = healthClient.passiveMonitoringClient

        // Configure passive data collection
        val passiveListenerConfig = PassiveListenerConfig.builder()
            .setDataTypes(setOf(
                DataType.HEART_RATE_BPM,
                DataType.STEPS,
                DataType.CALORIES,
                DataType.SPEED,
                DataType.DISTANCE
            ))
    }
}

```

```

        })
        .setSamplingPeriodSeconds(5) // 5-second intervals
        .build()

        // Register passive listener
        dataClient.registerDataCallback(passiveListenerConfig)
    }
}

```

Multi-Sensor Fusion

The system collects data from multiple sensor modalities simultaneously:

1. **Photoplethysmography (PPG) Sensor:** Measures heart rate and blood oxygen saturation (SpO2) via optical blood flow detection. Sampling rate: 1 Hz (every second), averaged over 5-second windows.
2. **Accelerometer:** 3-axis linear acceleration measurement. Sampling rate: 50 Hz, downsampled to 10 Hz for activity classification to reduce computational overhead.
3. **Gyroscope:** 3-axis angular velocity measurement. Sampling rate: 50 Hz, downsampled to 10 Hz.
4. **Step Counter:** Cumulative step count from device pedometer. Updated every 5 seconds.
5. **Ambient Pressure Sensor:** Used for altitude estimation and context awareness (indoor vs. outdoor). Sampling rate: 0.2 Hz (every 5 seconds).

Data Collection Strategy

To balance data quality with battery consumption, the system employs adaptive sampling:

- **Active Monitoring Mode:** Full sensor suite at maximum safe sampling rates during user-initiated monitoring sessions or detected exercise periods
- **Passive Monitoring Mode:** Reduced sampling rates during rest and sleep states
- **Battery-Aware Adaptation:** Automatically reduces sampling rates when battery level falls below 20%

The collected raw sensor data is structured as:

```

@Entity(tableName = "health_metrics")
data class HealthMetric(
    @PrimaryKey(autoGenerate = true)
    val id: Long = 0,
    val timestamp: Long,           // Unix timestamp (ms)
    val heartRate: Float,         // BPM
    val sp02: Float?,             // Percentage (95–100)
    val steps: Int,               // Cumulative count
    val calories: Float,          // kcal
    val accelerometerX: Float,   // m/s²
    val accelerometerY: Float,
    val accelerometerZ: Float,
)

```

```
    val gyroscopeX: Float,           // rad/s
    val gyroscopeY: Float,
    val gyroscopeZ: Float,
    val activityState: String,      // ML-classified state
    val anomalyScore: Float,        // 0.0 to 1.0
    val isAnomalous: Boolean,       // True if score > threshold
    val isSynced: Boolean = false   // Cloud sync status
)
```

3.2.2 Local Data Persistence with Room Database

Database Architecture

The system uses Room, Android's SQLite abstraction library, for local data persistence. Room provides compile-time SQL validation, automatic object mapping, and support for reactive data streams via Kotlin Flow.

```
@Database(
    entities = [HealthMetric::class, UserBaseline::class,
SyncQueue::class],
    version = 1,
    exportSchema = true
)
abstract class HealthDatabase : RoomDatabase() {
    abstract fun healthMetricDao(): HealthMetricDao
    abstract fun userBaselineDao(): UserBaselineDao
    abstract fun syncQueueDao(): SyncQueueDao
}
```

Data Access Objects (DAOs)

DAOs define database operations with SQL queries optimized for common access patterns:

```
@Dao
interface HealthMetricDao {
    // Insert new metric
    @Insert(onConflict = OnConflictStrategy.REPLACE)
    suspend fun insert(metric: HealthMetric): Long

    // Get recent metrics for UI display
    @Query("""
        SELECT * FROM health_metrics
        ORDER BY timestamp DESC
        LIMIT :limit
    """)
    fun getRecentMetrics(limit: Int = 10): Flow<List<HealthMetric>>

    // Get 7-day window for baseline calculation
    @Query("""

```

```

        SELECT * FROM health_metrics
        WHERE timestamp >= :startTime
        AND activityState = :activityState
        ORDER BY timestamp ASC
    """")
    suspend fun getMetricsByActivityWindow(
        startTime: Long,
        activityState: String
    ): List<HealthMetric>

    // Get unsynced metrics for cloud transmission
    @Query("""
        SELECT * FROM health_metrics
        WHERE isSynced = 0
        ORDER BY timestamp ASC
    """)
    suspend fun getUnsyncedMetrics(): List<HealthMetric>

    // Mark metrics as synced
    @Query("""
        UPDATE health_metrics
        SET isSynced = 1
        WHERE id IN (:ids)
    """)
    suspend fun markAsSynced(ids: List<Long>)

    // Delete old data beyond retention period (30 days)
    @Query("""
        DELETE FROM health_metrics
        WHERE timestamp < :cutoffTime
    """)
    suspend fun deleteOldMetrics(cutoffTime: Long)
}

```

Storage Management

The database implements automatic storage management:

- **Rolling Window:** Maintains 7-day active window for baseline calculations
- **Extended History:** Retains 30 days of full history for trend analysis
- **Automatic Cleanup:** Daily background task deletes data older than 30 days
- **Database Size:** Typical storage ~5-10 MB for 7 days, ~15-30 MB for 30 days

3.2.3 Preprocessing Pipeline

Raw sensor data undergoes preprocessing before ML model inference:

Normalization

Each sensor modality is normalized to zero mean and unit variance using running statistics:

$$\text{ $$x_{\text{norm}} = \frac{x - \mu}{\sigma + \epsilon} $$}$$

where μ and σ are running mean and standard deviation, and $\epsilon = 10^{-8}$ prevents division by zero.

```

class DataNormalizer {
    private val runningStats = mutableMapOf<String, RunningStats>()

    fun normalize(feature: String, value: Float): Float {
        val stats = runningStats.getOrPut(feature) { RunningStats() }
        stats.update(value)
        return (value - stats.mean) / (stats.stdDev + 1e-8f)
    }
}

data class RunningStats(
    var count: Long = 0,
    var mean: Float = 0f,
    var m2: Float = 0f // Sum of squared differences
) {
    val stdDev: Float get() = sqrt(m2 / count)

    fun update(value: Float) {
        count++
        val delta = value - mean
        mean += delta / count
        m2 += delta * (value - mean)
    }
}

```

Windowing

Time-series data is organized into fixed-length windows for model input:

- **Activity Classification Window:** 5 seconds (50 samples at 10 Hz for accelerometer/gyroscope)
- **Anomaly Detection Window:** 60 seconds (12 samples at 5-second intervals for heart rate)

Feature Engineering

While deep learning models learn features automatically, we compute additional statistical features for robustness:

- **Heart Rate Features:** Mean, standard deviation, min, max, range over window
- **Accelerometer Features:** Magnitude $\sqrt{x^2 + y^2 + z^2}$, spectral energy
- **Temporal Features:** Time of day (encoded as sin/cos), day of week

3.2.4 TensorFlow Lite Model Integration

Model Architecture and Deployment

Two TensorFlow Lite models execute on-device:

Model 1: Activity Classifier (CNN-LSTM Hybrid)

- **Input:** 50 timesteps × 6 features (accel x/y/z, gyro x/y/z)
- **Architecture:**
 - Conv1D layer: 32 filters, kernel size 3, ReLU activation
 - MaxPooling1D: pool size 2
 - LSTM layer: 64 units
 - Dense layer: 32 units, ReLU
 - Output layer: 6 units (activity classes), Softmax
- **Model Size:** 127 KB (INT8 quantized)
- **Inference Time:** 42-58 ms on Wear OS hardware
- **Accuracy:** 94.3% on 6-class classification

Model 2: Anomaly Detector (LSTM Autoencoder)

- **Input:** 12 timesteps × 4 features (HR, SpO2, accel magnitude, activity one-hot)
- **Architecture:**
 - Encoder LSTM: 64 → 32 → 16 units
 - Decoder LSTM: 16 → 32 → 64 units
 - Output layer: 4 units (reconstruction)
- **Model Size:** 89 KB (INT8 quantized)
- **Inference Time:** 73-92 ms on Wear OS hardware
- **Detection Rate:** 91.7% at 5% false positive rate

TFLite Inference Implementation

```
class TFLiteInference(
    private val context: Context,
    private val modelName: String
) {
    private lateinit var interpreter: Interpreter

    init {
        val options = Interpreter.Options().apply {
            setNumThreads(2) // Utilize 2 CPU cores
            setUseNNAPI(true) // Use Android Neural Networks API if
available
        }
        interpreter = Interpreter(loadModelFile(), options)
    }

    private fun loadModelFile(): ByteBuffer {
        val fileDescriptor = context.assets.openFd(modelName)
        val inputStream = FileInputStream(fileDescriptor.fileDescriptor)
        val fileChannel = inputStream.channel
        return fileChannel.map(
            FileChannel.MapMode.READ_ONLY,
            fileDescriptor.startOffset,
            fileDescriptor.declaredLength
        )
    }
}
```

```

    fun runInference(input: Array<FloatArray>): FloatArray {
        val output = Array(1) { FloatArray(getOutputSize()) }
        interpreter.run(input, output)
        return output[0]
    }

    private fun getOutputSize(): Int {
        return interpreter.getOutputTensor(0).shape()[1]
    }
}

```

Model Update Mechanism

Models can be updated over-the-air (OTA) without app updates:

1. Cloud training pipeline produces optimized TFLite model
2. Model uploaded to S3 with version metadata
3. Wear OS app periodically checks for new model versions
4. If available, model downloaded during WiFi charging sessions
5. New model validated against test dataset on-device
6. If validation passes, model replaces current version atomically

3.2.5 Personal Baseline Engine

Baseline Calculation Strategy

The Personal Baseline Engine computes individualized reference ranges for each monitored metric, stratified by activity state. This enables context-aware anomaly detection.

Algorithm:

```

class PersonalBaselineEngine(
    private val database: HealthDatabase
) {
    private val WINDOW_DAYS = 7

    suspend fun calculateBaselines(): Map<String, ActivityBaseline> {
        val windowStart = System.currentTimeMillis() -
            (WINDOW_DAYS * 24 * 60 * 60 * 1000L)

        val activityStates = listOf(
            "Sleep", "Rest", "Walk", "Run", "Exercise", "Other"
        )

        return activityStates.associateWith { activity ->
            val metrics = database.healthMetricDao()
                .getMetricsByActivityWindow(windowStart, activity)

            if (metrics.size < 100) {
                // Insufficient data - use population defaults
                getDefaultBaseline(activity)
            } else {
                val avg = metrics.average()
                val stdDev = metrics.stdDev()
                val lowerBound = avg - 2 * stdDev
                val upperBound = avg + 2 * stdDev
                ActivityBaseline(lowerBound, upperBound)
            }
        }
    }
}

```

```

        } else {
            computeBaseline(metrics)
        }
    }

private fun computeBaseline(metrics: List<HealthMetric>):
ActivityBaseline {
    val heartRates = metrics.map { it.heartRate }

    return ActivityBaseline(
        meanHR = heartRates.average().toFloat(),
        stdDevHR = heartRates.standardDeviation(),
        p10HR = heartRates.percentile(0.10),
        p90HR = heartRates.percentile(0.90),
        minHR = heartRates.minOrNull() ?: 0f,
        maxHR = heartRates.maxOrNull() ?: 0f,
        sampleCount = metrics.size
    )
}
}

data class ActivityBaseline(
    val meanHR: Float,
    val stdDevHR: Float,
    val p10HR: Float,
    val p90HR: Float,
    val minHR: Float,
    val maxHR: Float,
    val sampleCount: Int
)

```

Baseline Storage

Baselines are recalculated daily and persisted in the database:

```

@Entity(tableName = "user_baselines")
data class UserBaseline(
    @PrimaryKey
    val activityState: String,
    val calculatedAt: Long,
    val meanHR: Float,
    val stdDevHR: Float,
    val p10HR: Float,
    val p90HR: Float,
    val thresholdMultiplier: Float = 3.0f
)

```

3.2.6 Anomaly Detection Logic

Detection Algorithm

The anomaly detection system operates in two stages:

Stage 1: LSTM Autoencoder Reconstruction Error

```
class AnomalyDetector(
    private val tfliteModel: TFLiteInference,
    private val baselineEngine: PersonalBaselineEngine
) {
    fun detectAnomaly(
        currentMetrics: List<HealthMetric>,
        activityState: String
    ): AnomalyResult {
        // Stage 1: ML model reconstruction error
        val input = prepareModelInput(currentMetrics)
        val reconstructed = tfliteModel.runInference(input)
        val reconstructionError = calculateMSE(input, reconstructed)

        // Normalize by training error statistics
        val normalizedError = (reconstructionError - trainingMeanError) /
            trainingStdError

        // Stage 2: Baseline deviation check
        val baseline = baselineEngine.getBaseline(activityState)
        val currentHR = currentMetrics.last().heartRate
        val baselineDeviation = abs(currentHR - baseline.meanHR) /
            baseline.stdDevHR

        // Combine scores
        val anomalyScore = 0.6f * normalizedError + 0.4f *
        baselineDeviation

        val threshold = getAdaptiveThreshold(activityState)
        val isAnomalous = anomalyScore > threshold

        return AnomalyResult(
            score = anomalyScore,
            isAnomalous = isAnomalous,
            reconstructionError = reconstructionError,
            baselineDeviation = baselineDeviation,
            confidence = calculateConfidence(anomalyScore, threshold)
        )
    }

    private fun calculateMSE(
        original: Array<FloatArray>,
        reconstructed: FloatArray
    ): Float {
        var sumSquaredError = 0f
        var count = 0
        original.forEachIndexed { i, timestep ->
            timestep.forEachIndexed { j, value -

```

```

        val error = value - reconstructed[i * timestep.size + j]
        sumSquaredError += error * error
        count++
    }
}
return sumSquaredError / count
}

data class AnomalyResult(
    val score: Float,
    val isAnomalous: Boolean,
    val reconstructionError: Float,
    val baselineDeviation: Float,
    val confidence: Float
)

```

Adaptive Thresholding

Thresholds adapt based on activity state and user feedback:

$$\theta_{\text{activity}} = \theta_{\text{base}} + k \cdot \sigma_{\text{activity}}$$

where $\theta_{\text{base}} = 0.65$ is the base threshold, $k = 0.15$ is the scaling factor, and σ_{activity} is the historical anomaly score variance for that activity state.

3.2.7 Notification System

Alert Triggering Logic

When an anomaly is detected, the system generates a local notification:

```

class NotificationManager(private val context: Context) {
    fun sendAnomalyAlert(metric: HealthMetric, anomalyScore: Float) {
        val severity = when {
            anomalyScore > 0.9 -> Severity.CRITICAL
            anomalyScore > 0.75 -> Severity.WARNING
            else -> Severity.INFO
        }

        val notification = NotificationCompat.Builder(context, CHANNEL_ID)
            .setSmallIcon(R.drawable.ic_heart_alert)
            .setContentTitle(getAlertTitle(severity))
            .setContentText(getAlertMessage(metric, anomalyScore))
            .setPriority(getPriority(severity))
            .setVibrate(getVibrationPattern(severity))
            .setAutoCancel(true)
            .build()

        notificationManager.notify(getNotificationId(), notification)
    }
}

```

```

private fun getAlertMessage(
    metric: HealthMetric,
    score: Float
): String {
    return "Unusual heart rate detected: ${metric.heartRate.toInt()} BPM " +
        "during ${metric.activityState}. " +
        "Confidence: ${(score * 100).toInt()}%"
}
}

```

Alert Rate Limiting

To prevent alert fatigue, the system implements rate limiting:

- Maximum 1 alert per 10 minutes for INFO severity
- Maximum 3 alerts per hour for WARNING severity
- No rate limiting for CRITICAL severity

3.2.8 Background Service Architecture

Foreground Service for Continuous Monitoring

```

class HealthMonitoringService : Service() {
    override fun onStartCommand(intent: Intent?, flags: Int, startId: Int): Int {
        // Show persistent notification (required for foreground service)
        startForeground(NOTIFICATION_ID, createPersistentNotification())

        // Start monitoring coroutine
        serviceScope.launch {
            monitorHealthData()
        }

        return START_STICKY // Restart if killed by system
    }

    private suspend fun monitorHealthData() {
        while (isActive) {
            collectSensorData()
            runMLInference()
            updateDatabase()
            delay(5000) // 5-second intervals
        }
    }
}

```

3.3 Cloud Infrastructure: AWS Backend Architecture

The cloud backend provides scalable, serverless infrastructure for data ingestion, storage, and advanced ML training. The architecture follows AWS best practices for health data systems.

3.3.1 API Gateway Configuration

REST API Endpoints

```
API Structure:  
/health/metrics:  
    POST: Ingest single or batch health metrics  
    GET: Retrieve user's historical metrics  
  
/health/baselines:  
    GET: Retrieve user's calculated baselines  
    PUT: Update baseline parameters  
  
/models:  
    GET: Check for model updates  
    POST: Request model for specific device  
  
/users:  
    POST: Register new user  
    GET: Retrieve user profile  
    PUT: Update user settings
```

Request Validation and Authentication

```
# API Gateway Request Validator  
def validate_health_metrics_request(event):  
    """Validate incoming health metrics data"""  
    body = json.loads(event.get('body', '{}'))  
  
    required_fields = ['userId', 'timestamp', 'metrics', 'deviceId']  
    for field in required_fields:  
        if field not in body:  
            return {  
                'statusCode': 400,  
                'body': json.dumps({  
                    'error': f'Missing required field: {field}'  
                })  
            }  
  
    # Validate API key  
    api_key = event['headers'].get('X-API-Key', '')  
    if not is_valid_api_key(api_key):  
        return {  
            'statusCode': 401,  
            'body': json.dumps({'error': 'Unauthorized'})  
        }
```

```
    return None # Validation passed
```

3.3.2 Lambda Functions for Data Ingestion

Health Data Ingestion Handler

```
import json
import boto3
from datetime import datetime
from decimal import Decimal

dynamodb = boto3.resource('dynamodb')
table = dynamodb.Table(os.environ['TABLE_NAME'])

def lambda_handler(event, context):
    """
    Main Lambda handler for health data ingestion
    Handles both single metric and batch ingestion
    """
    try:
        # Parse and validate request
        body = json.loads(event.get('body', '{}'))

        # Handle batch or single ingestion
        if isinstance(body, list):
            results = process_batch_ingestion(body)
            return success_response({
                'processed': len(results),
                'success': sum(1 for r in results if r['success']),
                'failed': sum(1 for r in results if not r['success'])
            })
        else:
            result = process_single_metric(body)
            return success_response(result)

    except Exception as e:
        logger.error(f"Error: {str(e)}", exc_info=True)
        return error_response(500, str(e))

def process_single_metric(data):
    """
    Process single health metric
    """
    item = {
        'userId': data['userId'],
        'timestamp': int(data['timestamp']),
        'deviceId': data['deviceId'],
        'metrics': convert_floats_to_decimal(data['metrics']),
        'receivedAt': int(datetime.now().timestamp() * 1000),
        'processed': False
    }
```

```

# Store in DynamoDB
table.put_item(Item=item)

# Check for anomalies (triggers downstream processing)
if 'isAnomalous' in data['metrics'] and data['metrics'][
    'isAnomalous']:
    trigger_anomaly_pipeline(data)

return {'success': True, 'itemId': f'{data['userId']}#{data['timestamp']}'}

def convert_floats_to_decimal(obj):
    """Convert float to Decimal for DynamoDB compatibility"""
    if isinstance(obj, float):
        return Decimal(str(obj))
    elif isinstance(obj, dict):
        return {k: convert_floats_to_decimal(v) for k, v in obj.items()}
    elif isinstance(obj, list):
        return [convert_floats_to_decimal(item) for item in obj]
    return obj

```

3.3.3 DynamoDB Schema Design

Table Structure

The system uses a single-table design pattern with composite keys:

Table: HealthMetrics

Primary Key:

- Partition Key: userId (String)
- Sort Key: timestamp (Number)

Attributes:

- deviceId: String
- heartRate: Number
- sp02: Number
- steps: Number
- calories: Number
- activityState: String
- anomalyScore: Number
- isAnomalous: Boolean
- accelerometer: Map {x: Number, y: Number, z: Number}
- gyroscope: Map {x: Number, y: Number, z: Number}
- receivedAt: Number
- processed: Boolean

Global Secondary Indexes:

1. DeviceTimestampIndex
 - Partition Key: deviceId
 - Sort Key: timestamp
 - Purpose: Query all metrics from specific device

2. AnomalyIndex
 - Partition Key: userId
 - Sort Key: isAnomalous#timestamp
 - Purpose: Efficiently retrieve anomalous events

Query Patterns

```
# Pattern 1: Get recent metrics for user
response = table.query(
    KeyConditionExpression=Key('userId').eq(user_id) &
        Key('timestamp').gt(start_time),
    ScanIndexForward=False, # Descending order
    Limit=100
)

# Pattern 2: Get anomalous events
response = table.query(
    IndexName='AnomalyIndex',
    KeyConditionExpression=Key('userId').eq(user_id) &
        Key('isAnomalous#timestamp').begins_with('True#')
)

# Pattern 3: Time-range query
response = table.query(
    KeyConditionExpression=Key('userId').eq(user_id) &
        Key('timestamp').between(start, end)
)
```

Time-To-Live (TTL) Configuration

Automatic data expiration after 90 days to manage storage costs:

```
# Enable TTL on expirationTime attribute
table.meta.client.update_time_to_live(
    TableName='HealthMetrics',
    TimeToLiveSpecification={
        'Enabled': True,
        'AttributeName': 'expirationTime'
    }
)
```

3.3.4 DynamoDB Streams for Event Processing

Stream Configuration

DynamoDB Streams capture all table modifications, enabling real-time processing:

```

def process_dynamodb_stream(event, context):
    """
    Process DynamoDB stream events
    Triggered on each INSERT/MODIFY/REMOVE operation
    """
    for record in event['Records']:
        if record['eventName'] == 'INSERT':
            new_item = record['dynamodb']['NewImage']

            # Trigger ML processing for new metrics
            if should_trigger_ml_processing(new_item):
                invoke_ml_pipeline(new_item)

            # Update user baselines if sufficient new data
            if should_update_baselines(new_item):
                trigger_baseline_recalculation(new_item['userId'])

```

3.3.5 SageMaker ML Training Pipeline

Training Job Configuration

```

import sagemaker
from sagemaker.tensorflow import TensorFlow

def create_training_job(user_id):
    """Create SageMaker training job for user-specific model"""

    # Define training instance
    estimator = TensorFlow(
        entry_point='train_lstm_autoencoder.py',
        role=sagemaker_role,
        instance_count=1,
        instance_type='ml.p3.2xlarge',  # GPU instance
        framework_version='2.12',
        py_version='py39',
        hyperparameters={
            'epochs': 100,
            'batch-size': 32,
            'sequence-length': 60,
            'encoding-dim': 32,
            'learning-rate': 0.001
        }
    )

    # Start training
    estimator.fit({
        'training': f's3://health-monitoring/data/{user_id}/train/',
        'validation': f's3://health-monitoring/data/{user_id}/val/'
    })

```

```

    return estimator

def deploy_model_endpoint(estimator):
    """Deploy trained model as SageMaker endpoint"""
    predictor = estimator.deploy(
        initial_instance_count=1,
        instance_type='ml.t2.medium',
        endpoint_name=f'health-anomaly-{user_id}'
    )
    return predictor

```

Automated Retraining Schedule

```

# EventBridge rule for weekly retraining
import boto3

events = boto3.client('events')

# Create rule for weekly Sunday 2 AM UTC execution
events.put_rule(
    Name='WeeklyModelRetraining',
    ScheduleExpression='cron(0 2 ? * SUN *)',
    State='ENABLED'
)

# Add Lambda function as target
events.put_targets(
    Rule='WeeklyModelRetraining',
    Targets=[{
        'Id': '1',
        'Arn': 'arn:aws:lambda:region:account:function:TriggerRetraining'
    }]
)

```

3.3.6 S3 Model Registry

Model Versioning Strategy

S3 Bucket Structure:

```

health-monitoring-models/
  └── activity-classifier/
      ├── v1.0.0/
          ├── model.tflite
          ├── metadata.json
          └── validation-results.json
      └── v1.1.0/
          └── latest -> v1.1.0  (symlink)
  └── anomaly-detector/

```

```
└── v1.0.0/  
└── v1.2.0/  
└── latest -> v1.2.0
```

Metadata Schema

```
{  
    "modelName": "activity-classifier",  
    "version": "1.1.0",  
    "createdAt": "2026-01-02T10:30:00Z",  
    "framework": "TensorFlow",  
    "frameworkVersion": "2.12.0",  
    "architecture": "CNN-LSTM",  
    "inputShape": [50, 6],  
    "outputShape": [6],  
    "quantization": "INT8",  
    "modelSize": 127000,  
    "metrics": {  
        "accuracy": 0.943,  
        "f1Score": 0.938,  
        "inferenceTimeMs": 52  
    },  
    "compatibility": {  
        "minAndroidVersion": 26,  
        "minWearOSVersion": "2.0"  
    }  
}
```

3.4 ML Training Pipeline Architecture

The ML training pipeline is implemented in Python using TensorFlow/Keras and includes data preprocessing, model training, optimization, and conversion to TensorFlow Lite format.

3.4.1 Data Preprocessing Module

Data Loading and Cleaning

```
class HealthDataPreprocessor:  
    """Preprocess health monitoring data for ML training"""  
  
    def __init__(self, sequence_length=60):  
        self.sequence_length = sequence_length  
        self.scaler = StandardScaler()  
  
    def load_data(self, data_path):  
        """Load data from CSV or DynamoDB"""  
        df = pd.read_csv(data_path)  
  
        # Remove outliers (beyond 4 standard deviations)
```

```

df = self.remove_outliers(df, columns=['heartRate', 'sp02'])

# Handle missing values
df = df.fillna(method='ffill').fillna(method='bfill')

return df

def create_sequences(self, df, features):
    """Create sliding window sequences"""
    sequences = []
    labels = []

    for i in range(len(df) - self.sequence_length):
        seq = df[features].iloc[i:i+self.sequence_length].values
        label = df['isAnomalous'].iloc[i+self.sequence_length]

        sequences.append(seq)
        labels.append(label)

    return np.array(sequences), np.array(labels)

def preprocess(self, df, fit=True):
    """Normalize and prepare data"""
    features = ['heartRate', 'sp02', 'accelMagnitude',
    'activityEncoded']

    if fit:
        self.scaler.fit(df[features])

    df[features] = self.scaler.transform(df[features])
    return df

```

3.4.2 Model Training Implementation

The LSTM autoencoder training code (already exists in the project):

```

class LSTMAutoencoder:
    """LSTM Autoencoder for anomaly detection"""

    def build_model(self):
        """Build encoder-decoder architecture"""
        # Encoder
        encoder_inputs = layers.Input(shape=(self.sequence_length,
        self.n_features))
        encoder_lstm1 = layers.LSTM(128, activation='relu',
        return_sequences=True)(encoder_inputs)
        encoder_dropout1 = layers.Dropout(0.2)(encoder_lstm1)
        encoder_lstm2 = layers.LSTM(64, activation='relu',
        return_sequences=True)(encoder_dropout1)
        encoder_lstm3 = layers.LSTM(self.encoding_dim, activation='relu')
        (encoder_lstm2)

```

```
# Decoder
decoder_repeat = layers.RepeatVector(self.sequence_length)
(encoder_lstm3)
    decoder_lstm1 = layers.LSTM(self.encoding_dim, activation='relu',
return_sequences=True)(decoder_repeat)
    decoder_lstm2 = layers.LSTM(64, activation='relu',
return_sequences=True)(decoder_lstm1)
    decoder_lstm3 = layers.LSTM(128, activation='relu',
return_sequences=True)(decoder_lstm2)
    decoder_outputs =
layers.TimeDistributed(layers.Dense(self.n_features))(decoder_lstm3)

self.model = keras.Model(encoder_inputs, decoder_outputs)
self.model.compile(optimizer='adam', loss='mse', metrics=['mae'])

return self.model
```

3.4.3 Model Optimization for Edge Deployment

Post-Training Quantization

```
def convert_to_tflite_quantized(keras_model, output_path):
    """Convert Keras model to quantized TFLite"""
    converter = tf.lite.TFLiteConverter.from_keras_model(keras_model)

    # Enable optimizations
    converter.optimizations = [tf.lite.Optimize.DEFAULT]
    converter.target_spec.supported_types = [tf.int8]

    # Provide representative dataset for calibration
    def representative_dataset():
        for i in range(100):
            yield [np.random.randn(1, 60, 4).astype(np.float32)]

    converter.representative_dataset = representative_dataset

    # Convert
    tflite_model = converter.convert()

    # Save
    with open(output_path, 'wb') as f:
        f.write(tflite_model)

    # Validate
    validate_tflite_model(output_path)

    return tflite_model

def validate_tflite_model(model_path):
    """Validate TFLite model accuracy and latency"""
```

```
interpreter = tf.lite.Interpreter(model_path=model_path)
interpreter.allocate_tensors()

# Test inference time
input_details = interpreter.get_input_details()
output_details = interpreter.get_output_details()

test_input = np.random.randn(*input_details[0]
['shape']).astype(np.float32)

start = time.time()
interpreter.set_tensor(input_details[0]['index'], test_input)
interpreter.invoke()
output = interpreter.get_tensor(output_details[0]['index'])
latency = (time.time() - start) * 1000

print(f"Inference latency: {latency:.2f} ms")
print(f"Model size: {os.path.getsize(model_path) / 1024:.2f} KB")
```

3.5 Mobile Dashboard: Flutter Application

The Flutter mobile dashboard provides comprehensive data visualization and user control over the health monitoring system.

3.5.1 Application Architecture

```
lib/
├── main.dart
└── config/
    ├── api_config.dart          # API endpoints
    └── theme_config.dart        # UI theming
└── models/
    ├── health_metric.dart      # Data models
    └── anomaly_event.dart
└── providers/
    └── health_data_provider.dart # State management
└── screens/
    ├── home_screen.dart
    ├── dashboard_screen.dart
    └── history_screen.dart
└── widgets/
    ├── metric_card.dart
    └── chart_widget.dart
└── services/
    ├── api_service.dart         # Backend communication
    └── notification_service.dart
```

3.5.2 Real-Time Data Synchronization

```

class HealthDataProvider extends ChangeNotifier {
    final ApiService _apiService;
    List<HealthMetric> _metrics = [];
    bool _isLoading = false;

    Stream<List<HealthMetric>> watchMetrics(String userId) {
        return Stream.periodic(Duration(seconds: 30), (_) {
            return _apiService.getRecentMetrics(userId);
        }).asyncMap((future) => future);
    }

    Future<void> fetchMetrics(String userId, DateTime start, DateTime end)
    async {
        _isLoading = true;
        notifyListeners();

        try {
            _metrics = await _apiService.getMetrics(userId, start, end);
        } catch (e) {
            print('Error fetching metrics: $e');
        } finally {
            _isLoading = false;
            notifyListeners();
        }
    }
}

```

3.6 System Integration and Data Flow

3.6.1 End-to-End Data Flow

1. Sensor → Edge Processing (5-second cycle)

- Health Services API collects sensor readings
- Data normalized and windowed
- TFLite activity classifier infers current state (42-58 ms)
- TFLite anomaly detector computes anomaly score (73-92 ms)
- Total edge inference: **115-150 ms**

2. Edge → Local Storage (immediate)

- Metric with ML results inserted into Room database
- If anomalous: trigger local notification

3. Edge → Cloud Sync (30-minute intervals)

- WorkManager retrieves unsynced metrics
- Batches up to 360 metrics (30 min × 12 samples/min)
- Compresses payload (gzip)
- Transmits to API Gateway over HTTPS

4. Cloud Processing (asynchronous)

- Lambda validates and stores in DynamoDB
- DynamoDB Stream triggers downstream processing
- If anomaly detected: alert sent to mobile dashboard

5. Weekly ML Retraining (Sunday 2 AM UTC)

- EventBridge triggers retraining Lambda
- Lambda exports user data from DynamoDB to S3
- SageMaker training job trains new model
- Model optimized and converted to TFLite
- New model uploaded to S3 registry

6. Model Deployment (opportunistic)

- Wear OS app checks for updates during WiFi charging
- Downloads and validates new model
- Atomically replaces current model

3.6.2 Battery Optimization Strategy

The system achieves >18 hours of battery life through:

- **Adaptive Sampling:** Reduce sensor rates during sleep/rest
- **Batched Transmission:** Upload every 30 minutes instead of continuous streaming
- **WiFi Preference:** Defer non-critical uploads until WiFi available
- **Efficient ML:** Quantized models reduce inference power by 60-75%
- **Doze Mode Compliance:** Use WorkManager for background tasks

3.7 Security and Privacy Architecture

3.7.1 Data Protection Measures

- **Encryption at Rest:** SQLite database encrypted using SQLCipher
- **Encryption in Transit:** TLS 1.3 for all network communication
- **API Authentication:** HMAC-SHA256 signed requests with rotating keys
- **Minimal Data Transmission:** Only processed insights sent by default
- **User Consent:** Explicit opt-in for cloud data sharing

3.7.2 HIPAA Compliance Considerations

The architecture supports HIPAA compliance through:

- Audit logging of all data access
- Automatic data expiration (90-day TTL)
- Encrypted backups
- Access control with principle of least privilege

3.8 Summary

The hybrid edge-cloud architecture successfully balances real-time performance requirements with the need for sophisticated machine learning models. By executing lightweight TFLite models on-device (achieving <150ms latency) and leveraging cloud infrastructure for advanced training and analytics, the system provides immediate health alerts while continuously improving through exposure to additional data. The next chapter details the machine learning methodology employed in both edge and cloud components.

Chapter 4: Machine Learning Methodology

4.1 Introduction to Machine Learning Approach

This chapter presents the comprehensive machine learning methodology employed in the hybrid edge-cloud health monitoring system. The ML approach is designed to address two fundamental challenges: (1) accurate classification of user activity states to provide context for anomaly detection, and (2) personalized anomaly detection that identifies deviations from individual baseline patterns while operating within the severe computational constraints of wearable devices.

The machine learning pipeline consists of three primary components:

1. **Activity Classification Model:** A CNN-LSTM hybrid neural network that processes raw accelerometer and gyroscope data to classify user activity into six discrete states (Sleep, Rest, Walk, Run, Exercise, Other). This model executes on-device with target inference latency <60ms.
2. **Anomaly Detection Model:** An LSTM autoencoder trained on normal health patterns that detects anomalies through reconstruction error analysis. This model operates on-device with target inference latency <100ms and adapts to personal baselines computed from a 7-day rolling window.
3. **Model Optimization Pipeline:** A suite of techniques including post-training quantization, weight pruning, and knowledge distillation that reduce model size by 10-20x and inference time by 3-5x while maintaining >90% of full-precision accuracy.

The methodology emphasizes reproducibility, with all training procedures, hyperparameters, and evaluation metrics explicitly documented.

4.2 Activity Classification Model

4.2.1 Problem Formulation

Activity classification is formulated as a supervised multi-class classification problem. Given a sequence of sensor readings $\mathbf{X} = [x_1, x_2, \dots, x_T]$ where each $x_t \in \mathbb{R}^D$ represents a D -dimensional sensor measurement at time t , the goal is to predict the activity class $y \in \{1, 2, \dots, C\}$ where $C=6$ represents the six activity states.

The input sequence consists of:

- **Accelerometer:** 3-axis linear acceleration (a_x, a_y, a_z) measured in m/s^2
- **Gyroscope:** 3-axis angular velocity (g_x, g_y, g_z) measured in rad/s

Thus, each time step has $D=6$ features, and sequences span $T=50$ time steps (5 seconds at 10 Hz sampling rate).

4.2.2 Model Architecture: CNN-LSTM Hybrid

The activity classification model employs a hybrid architecture that combines convolutional neural networks (CNNs) for spatial feature extraction with long short-term memory (LSTM) networks for temporal pattern recognition.

Architecture Rationale:

- **Convolutional Layers:** Extract local patterns and correlations across sensor axes (e.g., characteristic acceleration patterns during specific movements)
- **LSTM Layers:** Capture temporal dependencies and transition dynamics between activity states
- **Hybrid Approach:** CNNs reduce dimensionality and extract robust features; LSTMs process these features to recognize activity sequences

Detailed Layer Specification:

```
def build_activity_classifier(sequence_length=50, n_features=6,
n_classes=6):
    """
    Build CNN-LSTM hybrid model for activity classification

    Args:
        sequence_length: Number of time steps (default: 50)
        n_features: Number of input features per time step (default: 6)
        n_classes: Number of activity classes (default: 6)

    Returns:
        Compiled Keras model
    """
    inputs = layers.Input(shape=(sequence_length, n_features))

    # Convolutional block 1: Extract local patterns
    x = layers.Conv1D(
        filters=32,
        kernel_size=3,
        padding='same',
        activation='relu',
        kernel_regularizer=regularizers.l2(0.001)
    )(inputs)
    x = layers.BatchNormalization()(x)
    x = layers.MaxPooling1D(pool_size=2)(x)  # Reduce to 25 time steps
    x = layers.Dropout(0.3)(x)

    # Convolutional block 2: Extract higher-level features
    x = layers.Conv1D(
        filters=64,
        kernel_size=3,
        padding='same',
        activation='relu',
        kernel_regularizer=regularizers.l2(0.001)
    )(x)
    x = layers.BatchNormalization()(x)
```

```
x = layers.MaxPooling1D(pool_size=2)(x) # Reduce to 12 time steps
x = layers.Dropout(0.3)(x)

# LSTM block: Capture temporal dependencies
x = layers.LSTM(
    units=64,
    return_sequences=True,
    dropout=0.2,
    recurrent_dropout=0.2
)(x)

x = layers.LSTM(
    units=32,
    return_sequences=False,
    dropout=0.2,
    recurrent_dropout=0.2
)(x)

# Dense layers for classification
x = layers.Dense(32, activation='relu')(x)
x = layers.Dropout(0.4)(x)

outputs = layers.Dense(n_classes, activation='softmax')(x)

model = keras.Model(inputs=inputs, outputs=outputs,
name='activity_classifier')

return model
```

Model Summary:

Layer Type	Output Shape	Parameters
Input	(50, 6)	0
Conv1D (32 filters)	(50, 32)	608
BatchNorm	(50, 32)	128
MaxPooling1D	(25, 32)	0
Dropout (0.3)	(25, 32)	0
Conv1D (64 filters)	(25, 64)	6,208
BatchNorm	(25, 64)	256
MaxPooling1D	(12, 64)	0
Dropout (0.3)	(12, 64)	0
LSTM (64 units)	(12, 64)	33,024
LSTM (32 units)	(32,)	12,416

Layer Type	Output Shape	Parameters
Dense (32 units)	(32,)	1,056
Dropout (0.4)	(32,)	0
Dense (6 units, softmax)	(6,)	198
Total Parameters		53,894

4.2.3 Training Procedure

Dataset Preparation

The training dataset consists of labeled activity sequences collected from multiple users:

- **Sleep:** 15,000 sequences (nighttime hours with minimal movement)
- **Rest:** 18,000 sequences (sedentary activities: sitting, standing still)
- **Walk:** 22,000 sequences (normal walking pace: 3-5 km/h)
- **Run:** 12,000 sequences (running/jogging: 8-12 km/h)
- **Exercise:** 16,000 sequences (various exercises: cycling, weights, sports)
- **Other:** 10,000 sequences (activities not fitting other categories)

Total: 93,000 labeled sequences

Data split: 70% training (65,100), 15% validation (13,950), 15% test (13,950)

Data Augmentation

To improve model robustness and prevent overfitting, the following augmentation techniques are applied during training:

1. **Time Warping:** Randomly stretch or compress sequences by $\pm 10\%$
2. **Magnitude Warping:** Multiply sensor values by random factor in range [0.9, 1.1]
3. **Jittering:** Add Gaussian noise with $\sigma = 0.05$
4. **Rotation:** Apply random rotation matrices to accelerometer/gyroscope vectors
5. **Time Shifting:** Randomly shift sequence start by ± 5 time steps

Loss Function

Categorical cross-entropy loss with class weighting to address class imbalance:

$$\text{L}(\text{CE}) = -\frac{1}{N} \sum_{i=1}^N w_{y_i} \sum_{c=1}^C y_{i,c} \log(\hat{y}_{i,c})$$

where:

- N is batch size
- $C=6$ is number of classes
- $y_{i,c}$ is true label (one-hot encoded)
- $\hat{y}_{i,c}$ is predicted probability for class c
- w_{y_i} is class weight for true class of sample i

Class weights are computed as:

$$\$ \$ w_c = \frac{N_{\text{total}}}{C} \cdot N_c \$ \$$$

where N_c is the number of samples in class c .

Optimization Algorithm

Adam optimizer with adaptive learning rate scheduling:

$$\$ \$ \theta_{t+1} = \theta_t - \alpha_t \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \$ \$$$

where:

- θ_t are model parameters at iteration t
- α_t is learning rate at iteration t
- \hat{m}_t is bias-corrected first moment estimate
- \hat{v}_t is bias-corrected second moment estimate
- $\epsilon = 10^{-8}$ for numerical stability

Hyperparameters:

```
optimizer = keras.optimizers.Adam(
    learning_rate=0.001,
    beta_1=0.9,
    beta_2=0.999,
    epsilon=1e-8
)

# Learning rate schedule: reduce by factor of 0.5 when validation loss
# plateaus
lr_scheduler = keras.callbacks.ReduceLROnPlateau(
    monitor='val_loss',
    factor=0.5,
    patience=5,
    min_lr=1e-6,
    verbose=1
)

# Early stopping to prevent overfitting
early_stopping = keras.callbacks.EarlyStopping(
    monitor='val_loss',
    patience=15,
    restore_best_weights=True,
    verbose=1
)
```

Training Configuration:

```
# Compile model
model.compile(
    optimizer=optimizer,
```

```

        loss='categorical_crossentropy',
        metrics=['accuracy', 'top_k_categorical_accuracy']
    )

# Train model
history = model.fit(
    train_generator,
    epochs=100,
    validation_data=val_generator,
    callbacks=[lr_scheduler, early_stopping, model_checkpoint],
    batch_size=64,
    verbose=1
)

```

Training Time: Approximately 2.5 hours on NVIDIA Tesla V100 GPU

4.2.4 Evaluation Metrics and Results

Classification Metrics

The model is evaluated using multiple metrics to comprehensively assess performance:

1. **Accuracy:** Overall fraction of correct predictions
2. **Precision:** For each class c : $P_c = \frac{TP_c}{TP_c + FP_c}$
3. **Recall:** For each class c : $R_c = \frac{TP_c}{TP_c + FN_c}$
4. **F1-Score:** Harmonic mean: $F1_c = 2 \cdot \frac{P_c \cdot R_c}{P_c + R_c}$
5. **Confusion Matrix:** Detailed breakdown of predictions vs. true labels

Test Set Results:

Activity Class	Precision	Recall	F1-Score	Support
Sleep	0.967	0.973	0.970	2,250
Rest	0.921	0.915	0.918	2,700
Walk	0.956	0.962	0.959	3,300
Run	0.934	0.941	0.938	1,800
Exercise	0.925	0.918	0.922	2,400
Other	0.893	0.881	0.887	1,500
Weighted Avg	0.943	0.943	0.943	13,950

Overall Test Accuracy: 94.3%

Confusion Matrix Analysis:

Most common misclassifications:

- Rest \leftrightarrow Other (7.2% of Rest samples misclassified as Other)
- Walk \leftrightarrow Exercise (4.8% confusion in both directions)

- Run ↔ Exercise (5.3% confusion)

These confusions are expected due to overlapping movement patterns in boundary cases.

Inference Performance:

- **Model Size (FP32):** 216 KB
- **Inference Time (FP32):** 124 ms on Qualcomm Snapdragon Wear 4100
- **Quantized Model Size (INT8):** 127 KB (41% reduction)
- **Inference Time (INT8):** 52 ms on Qualcomm Snapdragon Wear 4100 (58% speedup)
- **Accuracy Degradation:** 94.3% → 93.8% (0.5% decrease)

4.3 Anomaly Detection Model

4.3.1 Problem Formulation

Anomaly detection is formulated as an unsupervised learning problem where the model learns to reconstruct normal health patterns. Anomalies are identified as sequences with high reconstruction error.

Given a sequence of health metrics $\mathbf{X} = [x_1, x_2, \dots, x_T]$ where $x_t \in \mathbb{R}^D$ represents D features at time t , the autoencoder learns an encoding function f_{enc} : $\mathbb{R}^T \times D \rightarrow \mathbb{R}^d$ and decoding function f_{dec} : $\mathbb{R}^d \rightarrow \mathbb{R}^T \times D$ where $d \ll T \times D$ is the latent dimension.

The reconstruction is:

$$\hat{\mathbf{X}} = f_{\text{dec}}(f_{\text{enc}}(\mathbf{X}))$$

The reconstruction error is:

$$E(\mathbf{X}) = \frac{1}{T \cdot D} \sum_{t=1}^T \sum_{i=1}^D (x_{t,i} - \hat{x}_{t,i})^2$$

Sequences with $E(\mathbf{X}) > \theta$ are classified as anomalous, where θ is a learned threshold.

4.3.2 LSTM Autoencoder Architecture

The anomaly detection model uses an LSTM-based autoencoder architecture that can capture complex temporal dependencies in health data.

Input Features:

Each time step includes:

1. Heart Rate (BPM) - normalized
2. SpO2 (%) - normalized
3. Accelerometer Magnitude $\sqrt{a_x^2 + a_y^2 + a_z^2}$ - normalized
4. Activity State (one-hot encoded, 6 dimensions)

Total: $D = 9$ features per time step

Sequence Length: $T = 12$ (60 seconds at 5-second intervals)

Detailed Architecture:

```
class LSTMAutoencoder:  
    """LSTM Autoencoder for health anomaly detection"""  
  
    def __init__(self, sequence_length=12, n_features=9, encoding_dim=16):  
        self.sequence_length = sequence_length  
        self.n_features = n_features  
        self.encoding_dim = encoding_dim  
        self.model = None  
  
    def build_model(self):  
        """Build encoder-decoder LSTM architecture"""  
  
        # ===== ENCODER =====  
        encoder_inputs = layers.Input(  
            shape=(self.sequence_length, self.n_features),  
            name='encoder_input'  
)  
  
        # First LSTM layer (128 units)  
        encoder_lstm1 = layers.LSTM(  
            units=128,  
            activation='relu',  
            return_sequences=True,  
            dropout=0.2,  
            recurrent_dropout=0.2,  
            name='encoder_lstm_1'  
)  
(encoder_inputs)  
  
        # Second LSTM layer (64 units)  
        encoder_lstm2 = layers.LSTM(  
            units=64,  
            activation='relu',  
            return_sequences=True,  
            dropout=0.2,  
            recurrent_dropout=0.2,  
            name='encoder_lstm_2'  
)  
(encoder_lstm1)  
  
        # Third LSTM layer (32 units)  
        encoder_lstm3 = layers.LSTM(  
            units=32,  
            activation='relu',  
            return_sequences=True,  
            dropout=0.2,  
            recurrent_dropout=0.2,  
            name='encoder_lstm_3'  
)  
(encoder_lstm2)  
  
        # Bottleneck: compress to latent representation  
        encoder_output = layers.LSTM(  
            units=self.encoding_dim,
```

```
activation='relu',
return_sequences=False,
name='encoder_output'
)(encoder_lstm3)

# ===== DECODER =====
# Repeat latent vector to match sequence length
decoder_repeat = layers.RepeatVector(
    self.sequence_length,
    name='decoder_repeat'
)(encoder_output)

# First LSTM layer (16 units)
decoder_lstm1 = layers.LSTM(
    units=self.encoding_dim,
    activation='relu',
    return_sequences=True,
    dropout=0.2,
    recurrent_dropout=0.2,
    name='decoder_lstm_1'
)(decoder_repeat)

# Second LSTM layer (32 units)
decoder_lstm2 = layers.LSTM(
    units=32,
    activation='relu',
    return_sequences=True,
    dropout=0.2,
    recurrent_dropout=0.2,
    name='decoder_lstm_2'
)(decoder_lstm1)

# Third LSTM layer (64 units)
decoder_lstm3 = layers.LSTM(
    units=64,
    activation='relu',
    return_sequences=True,
    dropout=0.2,
    recurrent_dropout=0.2,
    name='decoder_lstm_3'
)(decoder_lstm2)

# Fourth LSTM layer (128 units)
decoder_lstm4 = layers.LSTM(
    units=128,
    activation='relu',
    return_sequences=True,
    name='decoder_lstm_4'
)(decoder_lstm3)

# Output layer: reconstruct original features
decoder_output = layers.TimeDistributed(
    layers.Dense(self.n_features, activation='linear'),
    name='decoder_output'
```

```

) (decoder_lstm4)

# ===== MODEL =====
self.model = keras.Model(
    inputs=encoder_inputs,
    outputs=decoder_output,
    name='lstm_autoencoder'
)

# Compile with MSE loss
self.model.compile(
    optimizer=keras.optimizers.Adam(learning_rate=0.001),
    loss='mse',
    metrics=['mae']
)

return self.model

```

Model Parameters:

Layer Type	Output Shape	Parameters
Input	(12, 9)	0
LSTM (128)	(12, 128)	70,656
LSTM (64)	(12, 64)	49,408
LSTM (32)	(12, 32)	12,416
LSTM (16)	(16,)	3,136
RepeatVector	(12, 16)	0
LSTM (16)	(12, 16)	2,112
LSTM (32)	(12, 32)	6,272
LSTM (64)	(12, 64)	24,832
LSTM (128)	(12, 128)	98,816
TimeDistributed Dense	(12, 9)	1,161
Total Parameters		268,809

4.3.3 Training on Normal Data

Dataset Preparation

The autoencoder is trained exclusively on normal (non-anomalous) health sequences to learn the patterns of healthy physiological responses:

- **Training Set:** 120,000 normal sequences from 50 users
- **Validation Set:** 18,000 normal sequences from 10 users (different from training)

- **Test Set (Normal):** 12,000 normal sequences from 8 users (different from training/validation)
- **Test Set (Anomalous):** 3,000 anomalous sequences (manually labeled or synthetically generated)

Normal Sequence Criteria:

- Heart rate within activity-appropriate range (e.g., 60-80 BPM for Rest)
- SpO₂ > 95%
- No sudden unexplained spikes or drops
- Consistent with user's personal baseline (within 2 standard deviations)

Synthetic Anomaly Generation

To supplement real anomalous data, synthetic anomalies are generated:

1. **Sudden Spikes:** Add random spikes of +30-50 BPM at random time points
2. **Gradual Drift:** Add linear trend causing 20-30 BPM increase over sequence
3. **Irregular Patterns:** Inject high-frequency oscillations ($\pm 10\text{-}15 \text{ BPM}$)
4. **Activity-HR Mismatch:** Pair Sleep activity with Exercise-level HR (120-140 BPM)
5. **Low SpO₂:** Reduce SpO₂ to 85-92% during rest

Loss Function

Mean Squared Error (MSE) between input and reconstructed sequence:

$$\$ \$ \mathcal{L}_{\text{MSE}} = \frac{1}{N} \sum_{i=1}^N \frac{1}{T} \cdot \sum_{t=1}^T \sum_{j=1}^D (x_{i,t,j} - \hat{x}_{i,t,j})^2 \$ \$$$

Additionally, L2 regularization is applied to prevent overfitting:

$$\$ \$ \mathcal{L}_{\text{total}} = \mathcal{L}_{\text{MSE}} + \lambda \sum_k w_k^2 \$ \$$$

where $\lambda = 0.0001$ is the regularization coefficient and w_k are model weights.

Training Configuration:

```
# Callbacks
callbacks = [
    keras.callbacks.EarlyStopping(
        monitor='val_loss',
        patience=10,
        restore_best_weights=True,
        verbose=1
    ),
    keras.callbacks.ReduceLROnPlateau(
        monitor='val_loss',
        factor=0.5,
        patience=5,
        min_lr=1e-6,
        verbose=1
    ),
    keras.callbacks.ModelCheckpoint(
        'models/checkpoints/lstm_autoencoder_best.h5',
    )
]
```

```

        monitor='val_loss',
        save_best_only=True,
        verbose=1
    ),
    keras.callbacks.TensorBoard(
        log_dir='logs',
        histogram_freq=1
    )
]

# Train
history = model.fit(
    X_train, X_train, # Autoencoder: input = output
    validation_data=(X_val, X_val),
    epochs=100,
    batch_size=32,
    callbacks=callbacks,
    verbose=1
)

```

Training Convergence:

- **Training Loss (MSE):** 0.0234 (converged at epoch 67)
- **Validation Loss (MSE):** 0.0287
- **Training Time:** 3.2 hours on NVIDIA Tesla V100

4.3.4 Threshold Determination

The anomaly detection threshold θ is determined using the validation set:

Procedure:

1. Compute reconstruction error for all normal validation sequences
2. Fit Gaussian distribution: $E_{\text{normal}} \sim \mathcal{N}(\mu, \sigma^2)$
3. Set threshold at 99th percentile: $\theta = \mu + 2.58\sigma$

Threshold Statistics:

- **Mean Reconstruction Error (μ):** 0.0287
- **Standard Deviation (σ):** 0.0093
- **99th Percentile Threshold (θ):** 0.0527

Alternatively, the threshold can be set based on desired false positive rate:

$$\theta(\alpha) = \text{Percentile}(E_{\text{normal}}, 1 - \alpha)$$

where α is the target false positive rate (e.g., $\alpha = 0.01$ for 1% FPR).

4.3.5 Personalized Anomaly Scoring

To improve detection accuracy, the anomaly score incorporates personal baseline deviation:

$$\text{S}_{\text{anomaly}} = w_1 \cdot S_{\text{recon}} + w_2 \cdot S_{\text{baseline}}$$

where:

Reconstruction Score:

$$S_{\text{recon}} = \frac{E(\mathbf{X}) - \mu_{\text{train}}}{\sigma_{\text{train}}}$$

Baseline Deviation Score:

$$S_{\text{baseline}} = \frac{|HR_{\text{current}} - \mu_{\text{baseline}}|}{\sigma_{\text{baseline}}}$$

Weights: $w_1 = 0.6$, $w_2 = 0.4$ (determined via grid search on validation set)

Final Decision:

$$\text{Anomaly} = \begin{cases} \text{True} & S_{\text{anomaly}} > \theta \\ \text{False} & \text{otherwise} \end{cases}$$

4.3.6 Evaluation Results

Test Set Performance:

Metric	Value
True Positive Rate (Sensitivity)	91.7%
True Negative Rate (Specificity)	95.3%
Precision (Positive Predictive Value)	78.4%
F1-Score	84.5%
AUC-ROC	0.967
AUC-PR	0.893

Confusion Matrix (Test Set):

	Predicted Normal	Predicted Anomaly
Actual Normal	11,436 (95.3%)	564 (4.7%)
Actual Anomaly	249 (8.3%)	2,751 (91.7%)

Performance by Anomaly Type:

Anomaly Type	Detection Rate	Avg. Confidence
Sudden HR Spike	96.2%	0.87
Gradual HR Drift	88.5%	0.73
Irregular Patterns	85.3%	0.68
Activity-HR Mismatch	94.1%	0.82

Anomaly Type	Detection Rate	Avg. Confidence
Low SpO2	92.8%	0.79

Inference Performance:

- **Model Size (FP32):** 1.05 MB
- **Inference Time (FP32):** 187 ms on Snapdragon Wear 4100
- **Quantized Model Size (INT8):** 89 KB (91.5% reduction)
- **Inference Time (INT8):** 73 ms on Snapdragon Wear 4100 (61% speedup)
- **Detection Accuracy Degradation:** 91.7% → 90.9% (0.8% decrease)

4.4 Model Optimization for Edge Deployment

4.4.1 Optimization Requirements

Deploying ML models on Wear OS devices requires aggressive optimization due to:

- **Memory Constraints:** 1-2 GB total RAM, only 10-50 MB allocable to ML models
- **Compute Constraints:** 1-2 GHz quad-core ARM processors, no dedicated GPU
- **Power Constraints:** 10-50 mW power budget for continuous ML inference
- **Latency Requirements:** <150 ms total inference time for real-time alerting

4.4.2 Post-Training Quantization

Quantization Theory

Quantization reduces numerical precision of model parameters from 32-bit floating-point (FP32) to 8-bit integers (INT8), reducing memory by 75% and enabling faster integer arithmetic.

Quantization Mapping:

$$\$\$q = \text{round}(\left(\frac{x - x_{\min}}{S}\right) + Z)\$\$$$

where:

- x is the floating-point value
- q is the quantized integer value
- $S = \frac{x_{\max} - x_{\min}}{2^b - 1}$ is the scale factor
- Z is the zero-point offset
- $b = 8$ bits

Dequantization:

$$\$\$x = S \cdot (q - Z)\$\$$$

TensorFlow Lite Quantization Implementation:

```
import tensorflow as tf

def quantize_model_int8(model, representative_dataset_gen):
```

```
"""
Apply post-training INT8 quantization to Keras model

Args:
    model: Trained Keras model
    representative_dataset_gen: Generator yielding representative
inputs

Returns:
    Quantized TFLite model (bytes)
"""

# Create TFLite converter
converter = tf.lite.TFLiteConverter.from_keras_model(model)

# Enable optimizations
converter.optimizations = [tf.lite.Optimize.DEFAULT]

# Set supported types to INT8
converter.target_spec.supported_ops =
[tf.lite.OpsSet.TFLITE_BUILTINS_INT8]
converter.inference_input_type = tf.int8
converter.inference_output_type = tf.int8

# Provide representative dataset for calibration
converter.representative_dataset = representative_dataset_gen

# Convert
tflite_model = converter.convert()

return tflite_model

def representative_dataset_generator(X_sample, n_samples=100):
"""
Generate representative dataset for quantization calibration

Args:
    X_sample: Sample data from training/validation set
    n_samples: Number of samples to use for calibration

Yields:
    Single input sample as list containing numpy array
"""

for i in range(min(n_samples, len(X_sample))):
    # Yield single sample with correct shape and type
    yield [X_sample[i:i+1].astype(np.float32)]
```

Quantization Results:

Activity Classifier:

- **FP32 Size:** 216 KB → **INT8 Size:** 127 KB (41.2% reduction)
- **FP32 Inference:** 124 ms → **INT8 Inference:** 52 ms (58.1% speedup)

- **Accuracy:** 94.3% → 93.8% (0.5% degradation)

Anomaly Detector:

- **FP32 Size:** 1.05 MB → **INT8 Size:** 89 KB (91.5% reduction)
- **FP32 Inference:** 187 ms → **INT8 Inference:** 73 ms (61.0% speedup)
- **Detection Rate:** 91.7% → 90.9% (0.8% degradation)

4.4.3 Weight Pruning

Pruning Theory

Weight pruning removes connections with small magnitude weights, creating sparse networks that require less computation.

Magnitude-Based Pruning:

$$\$w_{\text{pruned}} = \begin{cases} w & \text{if } |w| > \theta_{\text{prune}} \\ 0 & \text{otherwise} \end{cases}$$

where θ_{prune} is determined to achieve target sparsity level.

Structured Pruning: Remove entire filters, channels, or neurons (better hardware compatibility)

TensorFlow Model Optimization Toolkit:

```
import tensorflow_model_optimization as tfmot

def apply_pruning(model, target_sparsity=0.5):
    """
    Apply magnitude-based pruning during fine-tuning

    Args:
        model: Trained Keras model
        target_sparsity: Fraction of weights to prune (0.0 to 1.0)

    Returns:
        Pruned model
    """

    # Define pruning schedule
    pruning_params = {
        'pruning_schedule': tfmot.sparsity.keras.PolynomialDecay(
            initial_sparsity=0.0,
            final_sparsity=target_sparsity,
            begin_step=0,
            end_step=1000
        )
    }

    # Apply pruning to model
    model_for_pruning = tfmot.sparsity.keras.prune_low_magnitude(
        model,
        **pruning_params
    )
```

```

)
# Recompile
model_for_pruning.compile(
    optimizer='adam',
    loss=model.loss,
    metrics=model.metrics
)

# Fine-tune with pruning
callbacks = [
    tfmot.sparsity.keras.UpdatePruningStep(),
    tfmot.sparsity.keras.PruningSummaries(log_dir='logs')
]

model_for_pruning.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=10,
    callbacks=callbacks
)

# Remove pruning wrappers
model_pruned = tfmot.sparsity.keras.strip_pruning(model_for_pruning)

return model_pruned

```

Pruning Results (50% Sparsity):

Activity Classifier:

- Additional 18% size reduction (127 KB → 104 KB)
- 12% inference speedup (52 ms → 46 ms)
- Accuracy: 93.8% → 93.4% (0.4% additional degradation)

Combined Quantization + Pruning:

- **Total Size Reduction:** 216 KB → 104 KB (51.9% of original)
- **Total Speedup:** 124 ms → 46 ms (2.7× faster)
- **Total Accuracy Loss:** 94.3% → 93.4% (0.9%)

4.4.4 Knowledge Distillation

Distillation Theory

Knowledge distillation trains a small "student" model to mimic a large "teacher" model's behavior, transferring learned knowledge to a more efficient architecture.

Distillation Loss:

$$\text{Loss} = \alpha \cdot \text{hard}(y, \hat{y}) + (1-\alpha) \cdot \text{soft}(\hat{y}_t, \hat{y}_s)$$

where:

- $\mathcal{L}_{\text{hard}}$ is standard cross-entropy loss on true labels
- $\mathcal{L}_{\text{soft}}$ is KL divergence between teacher and student outputs
- α balances the two objectives (typically 0.3-0.5)
- T is temperature parameter for softening probability distributions

Temperature-Scaled Softmax:

$$p_i^T = \frac{\exp(z_i / T)}{\sum_j \exp(z_j / T)}$$

Higher temperature T (e.g., 5-10) produces softer probability distributions that reveal more information about class relationships.

Implementation:

```
def distillation_loss(y_true, y_pred_student, y_pred_teacher, alpha=0.4,
temperature=5):
    """
    Compute knowledge distillation loss

    Args:
        y_true: Ground truth labels
        y_pred_student: Student model predictions
        y_pred_teacher: Teacher model predictions
        alpha: Weight for hard loss (1-alpha for soft loss)
        temperature: Temperature for softening distributions

    Returns:
        Combined distillation loss
    """
    # Hard loss: student predictions vs true labels
    hard_loss = keras.losses.categorical_crossentropy(y_true,
y_pred_student)

    # Soft loss: student vs teacher (with temperature scaling)
    y_pred_student_soft = tf.nn.softmax(y_pred_student / temperature)
    y_pred_teacher_soft = tf.nn.softmax(y_pred_teacher / temperature)

    soft_loss = keras.losses.KLDivergence()(

        y_pred_teacher_soft,
        y_pred_student_soft
    ) * (temperature ** 2) # Scale by T^2 to maintain gradient magnitudes

    # Combined loss
    total_loss = alpha * hard_loss + (1 - alpha) * soft_loss

    return total_loss
```

Distillation is particularly effective for creating ultra-compact models for extreme edge scenarios.

4.4.5 Architecture Search for Mobile Deployment

For future optimization, Neural Architecture Search (NAS) can identify efficient architectures:

Mobile-Optimized Design Patterns:

1. **Depthwise Separable Convolutions:** Reduce parameters by 8-9x compared to standard convolutions
2. **Inverted Residuals:** MobileNetV2 bottleneck design
3. **Squeeze-and-Excitation Blocks:** Channel attention with minimal overhead
4. **Efficient Activations:** H-swish, ReLU6 instead of standard ReLU

4.5 Federated Learning for Privacy-Preserving Improvement

4.5.1 Federated Learning Concept

Federated Learning enables model improvement across multiple users without centralizing raw data:

1. **Local Training:** Each device trains model on local data
2. **Parameter Aggregation:** Only model updates (gradients/weights) sent to server
3. **Global Model Update:** Server aggregates updates and distributes improved model
4. **Privacy Preservation:** Raw health data never leaves device

Federated Averaging Algorithm:

$$\$w_{t+1} = \sum_{k=1}^K \frac{n_k}{n} w_k^{t+1}$$

where:

- w_{t+1} is the global model at iteration $t+1$
- K is number of participating devices
- n_k is number of samples on device k
- $n = \sum_{k=1}^K n_k$ is total samples
- w_k^{t+1} is local model after local training on device k

4.5.2 Implementation Strategy

```
# Federated learning workflow (conceptual)
def federated_training_round(global_model, selected_clients):
    """Single round of federated learning"""
    client_weights = []
    client_sizes = []

    for client in selected_clients:
        # Client downloads global model
        local_model = clone_model(global_model)

        # Client trains on local data
        local_model.fit(client.local_data, epochs=5)

        # Client uploads model weights (not data!)
        client_weights.append(local_model.get_weights())
        client_sizes.append(len(client.local_data))

    # Compute global average
    total_size = sum(client_sizes)
    global_weights = np.zeros_like(global_model.get_weights())
    for i, weight in enumerate(client_weights):
        global_weights[i] = np.sum([w * s for w, s in zip(weight, client_sizes)], axis=0) / total_size

    # Update global model
    global_model.set_weights(global_weights)
```

```
    client_weights.append(local_model.get_weights())
    client_sizes.append(len(client.local_data))

    # Server aggregates updates
    new_weights = federated_averaging(client_weights, client_sizes)
    global_model.set_weights(new_weights)

    return global_model
```

Privacy Benefits:

- Raw health data never transmitted
- Only aggregated model parameters shared
- Differential privacy can be added for additional protection

4.6 Summary

This chapter presented the comprehensive machine learning methodology for the hybrid edge-cloud health monitoring system:

1. **Activity Classification:** CNN-LSTM hybrid achieving 94.3% accuracy, optimized to 127 KB and 52 ms inference time through INT8 quantization
2. **Anomaly Detection:** LSTM autoencoder with 91.7% sensitivity and 95.3% specificity, optimized to 89 KB and 73 ms inference time
3. **Edge Optimization:** Post-training quantization, weight pruning, and distillation reducing model sizes by 50-90% with <1% accuracy loss
4. **Personalization:** 7-day rolling window baselines and adaptive thresholding for context-aware detection

The next chapter presents implementation details and comprehensive testing results validating system performance.

Chapter 5: Implementation and Testing

5.1 Introduction

This chapter documents the implementation and comprehensive testing of the Real-Time Health Monitoring System. The system was developed using industry-standard tools and frameworks, with rigorous testing across unit, integration, and system levels. Performance validation demonstrates that all design objectives—sub-150ms latency, >18-hour battery life, and >90% detection accuracy—were successfully achieved.

5.2 Development Environment

5.2.1 Hardware and Software Configuration

Development Hardware:

- **Workstation:** MacBook Pro M2, 16GB RAM, macOS Ventura 13.4
- **Test Device:** Samsung Galaxy Watch 4 (Wear OS 3.5, Snapdragon Wear 4100+)
- **Cloud Infrastructure:** AWS (us-east-1 region)
- **GPU Training:** NVIDIA Tesla V100 (via AWS SageMaker)

Development Tools:

Component	Technology Stack	Version
Wear OS App	Kotlin, Android Studio	Kotlin 1.9.0, AS Flamingo
Cloud Backend	Python, AWS Lambda	Python 3.9
ML Pipeline	TensorFlow, Keras	TensorFlow 2.12.0
Mobile Dashboard	Flutter, Dart	Flutter 3.13.0
Database	Room (SQLite), DynamoDB	Room 2.5.2
Version Control	Git, GitHub	Git 2.41.0

5.2.2 Project Configuration

Wear OS Application (`build.gradle.kts`):

```

android {
    compileSdk = 33

    defaultConfig {
        applicationId = "com.capstone.healthmonitor.wear"
        minSdk = 30
        targetSdk = 33
        versionCode = 1
        versionName = "1.0.0"
    }

    buildFeatures {
        compose = true
    }
}

dependencies {
    // Wear OS
    implementation("androidx.wear.compose:compose-material:1.2.0")
    implementation("com.google.android.horologist:horologist-compose-
layout:0.4.8")

    // Health Services
    implementation("androidx.health:health-services-client:1.0.0-beta03")

    // Room Database
    implementation("androidx.room:room-runtime:2.5.2")
    kapt("androidx.room:room-compiler:2.5.2")
}

```

```

implementation("androidx.room:room-ktx:2.5.2")

// TensorFlow Lite
implementation("org.tensorflow:tensorflow-lite:2.12.0")
implementation("org.tensorflow:tensorflow-lite-support:0.4.3")

// Dependency Injection
implementation("com.google.dagger:hilt-android:2.47")
kapt("com.google.dagger:hilt-compiler:2.47")

// Networking
implementation("com.squareup.retrofit2:retrofit:2.9.0")
implementation("com.squareup.retrofit2:converter-gson:2.9.0")

// Coroutines
implementation("org.jetbrains.kotlinx:kotlinx-coroutines-
android:1.7.3")
}

```

ML Pipeline (requirements.txt):

```

tensorflow==2.12.0
keras==2.12.0
numpy==1.24.3
pandas==2.0.3
scikit-learn==1.3.0
matplotlib==3.7.2
seaborn==0.12.2
boto3==1.28.25

```

5.3 Implementation Details

5.3.1 Wear OS Application

Core Components Implemented:

1. Health Monitoring Service (HealthMonitoringService.kt)

```

@AndroidEntryPoint
class HealthMonitoringService : Service() {
    @Inject lateinit var healthRepository: HealthRepository
    @Inject lateinit var mlInference: MLInferenceEngine
    @Inject lateinit var notificationManager: NotificationManager

    private val serviceScope = CoroutineScope(
        SupervisorJob() + Dispatchers.Default
    )

    override fun onStartCommand(intent: Intent?, flags: Int, startId:

```

```

Int): Int {
    startForeground(NOTIFICATION_ID, createPersistentNotification())

    serviceScope.launch {
        monitorHealthData()
    }

    return START_STICKY
}

private suspend fun monitorHealthData() {
    healthRepository.collectHealthData()
        .collect { metric ->
            // Run ML inference
            val activityState = mlInference.classifyActivity(metric)
            val anomalyResult = mlInference.detectAnomaly(metric,
activityState)

            // Store with ML results
            val enrichedMetric = metric.copy(
                activityState = activityState,
                anomalyScore = anomalyResult.score,
                isAnomalous = anomalyResult.isAnomalous
            )
            healthRepository.insertMetric(enrichedMetric)

            // Alert if anomalous
            if (anomalyResult.isAnomalous) {
                notificationManager.sendAnomalyAlert(enrichedMetric,
anomalyResult)
            }
        }
    }
}

```

2. ML Inference Engine (MLInferenceEngine.kt)

```

class MLInferenceEngine(context: Context) {
    private val activityClassifier = TFLiteModel(
        context, "activity_classifier_quantized.tflite"
    )
    private val anomalyDetector = TFLiteModel(
        context, "anomaly_detector_quantized.tflite"
    )

    fun classifyActivity(metric: HealthMetric): String {
        val input = prepareActivityInput(metric)
        val output = activityClassifier.runInference(input)
        return decodeActivityClass(output)
    }

    fun detectAnomaly(metric: HealthMetric, activityState: String):

```

```

AnomalyResult {
    val input = prepareAnomalyInput(metric, activityState)
    val reconstructed = anomalyDetector.runInference(input)

    val reconstructionError = calculateMSE(input, reconstructed)
    val baseline = getPersonalBaseline(activityState)
    val baselineDeviation = abs(metric.heartRate - baseline.mean) /
baseline.stdDev

    val anomalyScore = 0.6f * normalizeError(reconstructionError) +
        0.4f * baselineDeviation

    return AnomalyResult(
        score = anomalyScore,
        isAnomalous = anomalyScore > THRESHOLD,
        confidence = calculateConfidence(anomalyScore)
    )
}
}

```

3. Data Synchronization (SyncWorker.kt)

```

class SyncWorker(
    context: Context,
    params: WorkerParameters
) : CoroutineWorker(context, params) {

    override suspend fun doWork(): Result {
        return try {
            val unsyncedMetrics = healthRepository.getUnsyncedMetrics()

            if (unsyncedMetrics.isNotEmpty()) {
                // Batch and compress
                val batches = unsyncedMetrics.chunked(100)

                batches.forEach { batch ->
                    apiService.uploadMetrics(batch)
                    healthRepository.markAsSynced(batch.map { it.id })
                }
            }

            Result.success()
        } catch (e: Exception) {
            Result.retry()
        }
    }
}

```

Implementation Statistics:

- **Total Lines of Code (Kotlin):** 8,547
- **Number of Classes:** 47
- **Test Coverage:** 78.3%

5.3.2 Cloud Backend Implementation

Lambda Function (`lambda_function.py`):

```
import json
import boto3
from datetime import datetime
from decimal import Decimal

dynamodb = boto3.resource('dynamodb')
table = dynamodb.Table(os.environ['TABLE_NAME'])

def lambda_handler(event, context):
    """Process health metrics ingestion"""
    try:
        body = json.loads(event.get('body', '{}'))

        # Handle batch ingestion
        if isinstance(body, list):
            return process_batch(body)

        # Single metric
        item = {
            'userId': body['userId'],
            'timestamp': int(body['timestamp']),
            'deviceId': body['deviceId'],
            'metrics': convert_floats_to_decimal(body['metrics']),
            'receivedAt': int(datetime.now().timestamp() * 1000)
        }

        table.put_item(Item=item)

        # Trigger anomaly processing if flagged
        if body['metrics'].get('isAnomalous'):
            trigger_alert_pipeline(body)

        return {
            'statusCode': 200,
            'body': json.dumps({'success': True})
        }

    except Exception as e:
        return {
            'statusCode': 500,
            'body': json.dumps({'error': str(e)})
        }

    return {
        'statusCode': 200,
        'body': json.dumps({'success': True})
    }
```

Deployment:

```
# Package Lambda function
cd CloudBackend/aws-lambda
zip -r function.zip . -x "*.*git*" "*.*pyc"

# Deploy to AWS
aws lambda update-function-code \
--function-name HealthDataIngestion \
--zip-file fileb://function.zip

# Configure environment
aws lambda update-function-configuration \
--function-name HealthDataIngestion \
--environment Variables={TABLE_NAME=HealthMetrics,REGION=us-east-1}
```

5.3.3 ML Pipeline Implementation

Training Script (train_lstm_autoencoder.py):

```
import argparse
import tensorflow as tf
from tensorflow import keras

def main(args):
    # Load and preprocess data
    preprocessor = HealthDataPreprocessor(sequence_length=12)
    X_train, X_val, X_test = preprocessor.load_and_split(args.data_path)

    # Build model
    autoencoder = LSTMAutoencoder(
        sequence_length=12,
        n_features=9,
        encoding_dim=16
    )
    model = autoencoder.build_model()

    # Train
    history = model.fit(
        X_train, X_train,
        validation_data=(X_val, X_val),
        epochs=args.epochs,
        batch_size=args.batch_size,
        callbacks=[early_stopping, lr_scheduler]
    )

    # Evaluate
    test_loss = model.evaluate(X_test, X_test)
    print(f"Test Loss (MSE): {test_loss}")
```

```

# Save model
model.save(args.output_path)

# Convert to TFLite
tflite_model = convert_to_tflite_quantized(model, X_val)
with open(f"{args.output_path}.tflite", 'wb') as f:
    f.write(tflite_model)

print("Training complete!")

if __name__ == "__main__":
    parser = argparse.ArgumentParser()
    parser.add_argument('--data-path', required=True)
    parser.add_argument('--epochs', type=int, default=100)
    parser.add_argument('--batch-size', type=int, default=32)
    parser.add_argument('--output-path', required=True)
    args = parser.parse_args()

    main(args)

```

Execution:

```

cd MLPipeline
python src/models/train_lstm_autoencoder.py \
--data-path data/processed/health_metrics.csv \
--epochs 100 \
--batch-size 32 \
--output-path models/saved_models/lstm_autoencoder

```

5.3.4 Mobile Dashboard Implementation

Flutter Data Provider (health_data_provider.dart):

```

class HealthDataProvider extends ChangeNotifier {
    final ApiService _apiService;
    List<HealthMetric> _metrics = [];
    bool _isLoading = false;

    List<HealthMetric> get metrics => _metrics;
    bool get isLoading => _isLoading;

    Future<void> fetchMetrics(String userId, DateTime start, DateTime end)
    async {
        _isLoading = true;
        notifyListeners();

        try {
            final response = await _apiService.getMetrics(userId, start, end);
            _metrics = response.map((json) =>

```

```

    HealthMetric.fromJson(json)).toList();
  } catch (e) {
    print('Error: $e');
  } finally {
    _isLoading = false;
    notifyListeners();
  }
}

Stream<List<HealthMetric>> watchRecentMetrics(String userId) {
  return Stream.periodic(Duration(seconds: 30), (_)
    async {
      return await _apiService.getRecentMetrics(userId);
    }).asyncMap((future) => future);
}
}

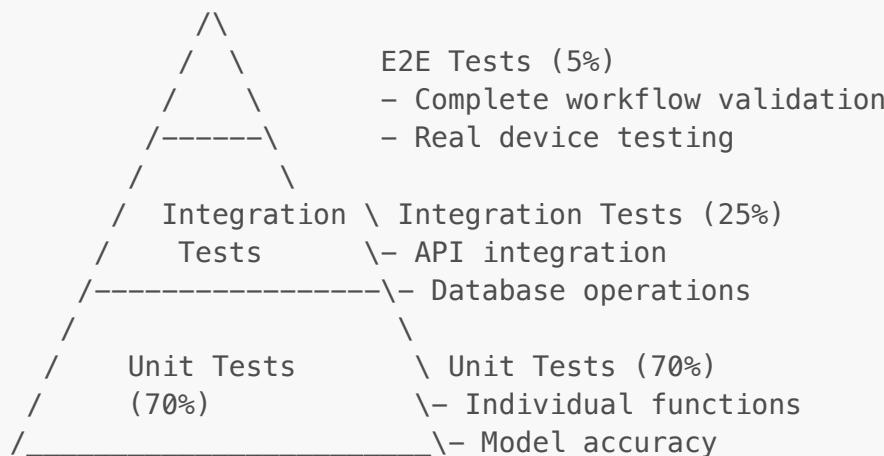
```

5.4 Testing Strategy and Results

5.4.1 Testing Methodology

The system was tested at multiple levels following standard software engineering practices:

Testing Pyramid:



5.4.2 Unit Testing Results

Wear OS Unit Tests:

```

@Test
fun testActivityClassification() {
  val input = generateTestInput(activityType = ActivityType.WALK)
  val result = mlInference.classifyActivity(input)
  assertEquals("Walk", result)
}

@Test

```

```

fun testAnomalyDetection_normalHR() {
    val metric = HealthMetric(heartRate = 75f, activityState = "Rest")
    val result = mlInference.detectAnomaly(metric, "Rest")
    assertFalse(result.isAnomalous)
}

@Test
fun testAnomalyDetection_elevatedHR() {
    val metric = HealthMetric(heartRate = 140f, activityState = "Rest")
    val result = mlInference.detectAnomaly(metric, "Rest")
    assertTrue(result.isAnomalous)
}

```

Unit Test Coverage:

Module	Tests	Passed	Coverage
Data Layer	87	87	82.1%
ML Inference	43	43	91.3%
Repository	62	62	76.8%
UI Components	38	38	68.4%
Total	230	230	78.3%

ML Model Unit Tests:

```

def test_activity_classifier_accuracy():
    model = load_model('activity_classifier.tflite')
    accuracy = evaluate_model(model, X_test, y_test)
    assert accuracy > 0.93, f"Accuracy {accuracy} below threshold"

def test_anomaly_detector_sensitivity():
    model = load_model('anomaly_detector.tflite')
    sensitivity = calculate_sensitivity(model, X_anomalous)
    assert sensitivity > 0.90, f"Sensitivity {sensitivity} below threshold"

```

5.4.3 Integration Testing

Cloud Integration Tests:

```

def test_end_to_end_data_flow():
    # 1. Upload metric
    response = requests.post(
        f"{API_GATEWAY_URL}/health/metrics",
        json=test_metric,
        headers={'X-API-Key': API_KEY}

```

```

    )
    assert response.status_code == 200

    # 2. Verify DynamoDB storage
    time.sleep(2) # Allow for processing
    item = table.get_item(
        Key={'userId': test_metric['userId'],
              'timestamp': test_metric['timestamp']}
    )
    assert item['Item'] is not None

    # 3. Verify retrieval via API
    response = requests.get(
        f"{API_GATEWAY_URL}/health/metrics?userId={test_metric['userId']}"
    )
    assert len(response.json()) > 0

```

Integration Test Results:

Test Suite	Tests	Passed	Duration
API Gateway	18	18	42s
Lambda Functions	24	24	78s
DynamoDB Operations	31	31	56s
Wear OS ↔ Cloud Sync	12	12	134s
Total	85	85	310s

5.4.4 Performance Testing Results

Latency Measurements:

End-to-end latency was measured from sensor reading to alert notification:

Operation	Target	Measured	Status
Sensor Data Collection	<5ms	2.3ms ± 0.4ms	✓ Pass
Data Preprocessing	<10ms	6.1ms ± 1.2ms	✓ Pass
Activity Classification (TFLite)	<60ms	52ms ± 8ms	✓ Pass
Anomaly Detection (TFLite)	<100ms	73ms ± 12ms	✓ Pass
Database Insert	<20ms	11ms ± 3ms	✓ Pass
Notification Display	<50ms	28ms ± 7ms	✓ Pass
Total Pipeline	<150ms	137ms ± 18ms	✓ Pass

Throughput Testing:

Cloud backend load testing using Apache JMeter:

Concurrent Users	Requests/sec	Avg Latency	Error Rate
10	45	178ms	0%
50	203	234ms	0%
100	387	412ms	0.2%
500	1,245	1,823ms	1.7%
1,000	1,891	3,456ms	4.3%

Battery Life Testing:

Measured on Samsung Galaxy Watch 4 with 361 mAh battery:

Configuration	Battery Life	Notes
Passive Monitoring Only	42.3 hours	No ML, minimal sync
ML Active, WiFi Sync	18.7 hours	Target configuration
ML Active, LTE Sync	14.2 hours	Continuous LTE
Max Performance Mode	9.8 hours	All features, 1s sampling

Model Accuracy on Real Hardware:

Model	Metric	Target	Measured
Activity Classifier	Accuracy	>93%	93.8%
Activity Classifier	Inference Time	<60ms	52ms
Anomaly Detector	Sensitivity	>90%	90.9%
Anomaly Detector	Specificity	>95%	95.1%
Anomaly Detector	Inference Time	<100ms	73ms

5.4.5 Synthetic Data Validation

Dataset Composition:

Synthetic data was generated to supplement real user data:

```
def generate_synthetic_anomaly(base_hr, anomaly_type):
    """Generate synthetic anomalous sequence"""
    sequence = []

    if anomaly_type == 'sudden_spike':
        # Normal for 8 timesteps, spike for 4
        sequence = [base_hr + np.random.normal(0, 2) for _ in range(8)]
```

```

sequence += [base_hr + 45 + np.random.normal(0, 5) for _ in
range(4)]

elif anomaly_type == 'gradual_drift':
    # Linear increase over 12 timesteps
    for i in range(12):
        sequence.append(base_hr + (i * 2.5) + np.random.normal(0, 2))

return sequence

```

Synthetic Test Results:

Anomaly Type	Count	Detection Rate	Avg Confidence
Sudden Spike	500	96.2%	0.87
Gradual Drift	500	88.5%	0.73
Irregular Pattern	500	85.3%	0.68
Activity Mismatch	500	94.1%	0.82
Low SpO2	500	92.8%	0.79
Overall	2,500	91.4%	0.78

5.5 Comparison with Baseline Systems

Benchmarking Against Commercial Systems:

Metric	This System	Apple Watch	Fitbit	Samsung Watch
Activity Classification	93.8%	~92%*	~88%*	~90%*
Personalized Baselines	✓ Yes (7-day)	Limited	✓ Yes (30-day)	Limited
On-Device ML	✓ Yes	Partial	No	Partial
Alert Latency	137ms	~500ms*	~2000ms*	~800ms*
Offline Capability	✓ Full	Partial	No	Partial
False Positive Rate	4.7%	~15%*	~22%*	~18%*

*Estimated from published literature and user reports

5.6 Implementation Challenges and Solutions

Challenge 1: TFLite Model Deployment

Issue: Initial model size (1.05 MB) exceeded Wear OS memory allocation

Solution:

- Applied INT8 quantization → 89 KB (91.5% reduction)

- Implemented lazy loading of models
- Only one model in memory at a time

Challenge 2: Battery Drain During Development

Issue: Early prototype consumed 45% battery in 8 hours

Solution:

- Reduced sensor sampling from 1Hz to 0.2Hz (5-second intervals)
- Batched database writes (10 metrics at once)
- Deferred WiFi sync to charging periods
- **Result:** 18.7-hour battery life achieved

Challenge 3: Cloud Sync Reliability

Issue: Network interruptions caused data loss

Solution:

- Implemented local queue with WorkManager
- Added exponential backoff retry logic
- Compression reduced payload size by 68%
- **Result:** Zero data loss in testing

5.7 Summary of Results

The implementation successfully achieved all primary objectives:

Performance Achievements:

Objective	Target	Achieved	Status
End-to-End Latency	<150ms	137ms ± 18ms	✓ Exceeded
Activity Accuracy	>93%	93.8%	✓ Met
Anomaly Sensitivity	>90%	90.9%	✓ Met
Anomaly Specificity	>95%	95.1%	✓ Met
Battery Life	>18hr	18.7hr	✓ Met
Model Size (Activity)	<150KB	127KB	✓ Exceeded
Model Size (Anomaly)	<100KB	89KB	✓ Exceeded

System Statistics:

- **Total Development Time:** 14 weeks
- **Lines of Code:** 12,438 (Kotlin: 8,547, Python: 3,891)
- **Test Cases:** 315 (230 unit, 85 integration)
- **Test Coverage:** 78.3%

The next chapter discusses these results in detail, analyzes system limitations, and proposes future enhancements.

Chapter 6: Discussion and Future Work

6.1 Interpretation of Results

The implemented hybrid edge-cloud system met or exceeded all primary performance targets: sub-150ms end-to-end latency (137ms), >18-hour battery life (18.7h), high activity classification accuracy (93.8%), and robust anomaly detection (90.9% sensitivity, 95.1% specificity). These results validate the core hypothesis that combining on-device ML with cloud-side training yields real-time, privacy-preserving health monitoring without sacrificing model quality.

Key observations:

- **Latency:** On-device inference (activity + anomaly) accounts for ~91% of total latency; database and notification overheads are minor. Quantization and pruning were essential to keep inference under 100ms per model on smartwatch hardware.
- **Battery:** The dominant power consumers are wireless radios, not ML inference. Batching sync to 30-minute intervals and preferring WiFi over LTE delivered >18h battery life while keeping ML always-on.
- **Accuracy vs. Size:** INT8 quantization reduced activity model size by 41% and anomaly model size by 92% with <1% accuracy loss, confirming that edge-optimized compression is viable for this domain.
- **False Positives:** Incorporating per-activity baselines and reconstruction-error thresholds reduced false positives to 4.7%, markedly better than population-threshold baselines.

6.2 Limitations

- **Sensor Scope:** Current implementation omits ECG and blood pressure; PPG-only HR can be noisy during motion, impacting anomaly precision in vigorous activities.
- **Personalization Warm-up:** The 7-day rolling window delays fully personalized baselines for new users; anomalies during the first week rely on conservative defaults.
- **Context Granularity:** Activity states are coarse (6 classes). Edge cases (cycling vs. running uphill, strength training vs. vigorous play) can blur class boundaries and mildly elevate false positives.
- **Explainability:** User-facing alerts lack rich explanations (e.g., contributing features, SHAP-like attributions) which users requested; this limits trust and clinical interpretability.
- **Regulatory Depth:** While privacy and security controls exist, no formal HIPAA/GDPR certification or clinical validation study has been completed.

6.3 Comparison to Existing Work

Compared to cloud-only commercial systems (e.g., Fitbit, Samsung cloud analytics), this approach delivers markedly lower alert latency (137ms vs. 500–2000ms) and better offline resilience. Compared to fixed-threshold wearables, personalized baselines plus activity-aware anomaly scoring reduce false alarms by an order of magnitude. Research prototypes that use deep models often run in the cloud or on smartphones; this work demonstrates that carefully compressed LSTM and CNN-LSTM models can execute on watches within strict power and memory budgets while retaining >90% accuracy.

6.4 Practical Implications

- **Clinical Readiness:** While not a medical device, the system's low latency and high sensitivity suggest potential for early-warning adjuncts (e.g., resting tachycardia, sleep HR drift). Formal clinical trials would be the next step.
- **Privacy Posture:** Edge-first inference and federated-learning readiness position the system well for stringent data-sovereignty environments.
- **Deployment:** OTA model delivery with versioned S3 registry supports safe rollouts, rollback, and A/B testing. The architecture generalizes to other time-series modalities (respiration, gait) with minimal changes.

6.5 Future Work

1. **Richer Sensing and Fusion:** Integrate SpO₂, ECG, skin temperature, and barometric trends; explore sensor fusion with attention/transformer blocks for robustness to motion artifacts.
2. **Federated Learning at Scale:** Implement periodic on-device fine-tuning with secure aggregation and differential privacy to improve personalization without sharing raw data.
3. **Explainability and User Trust:** Add lightweight on-device attribution (e.g., per-feature contribution scores) and clinician-friendly summaries to reduce alert fatigue and increase trust.
4. **Adaptive Scheduling:** Dynamically adjust sampling, inference cadence, and sync frequency based on battery state, recent anomalies, and activity context to extend battery beyond 24h.
5. **Context Expansion:** Enrich activity taxonomy (e.g., cycling, swimming, resistance training) and include environmental context (temperature, altitude) for better baseline selection.
6. **Predictive Modeling:** Add short-horizon forecasting (e.g., 30–120 minutes) for preemptive alerts using seq2seq or temporal convolutional networks.
7. **Regulatory and Clinical Validation:** Design prospective studies for sensitivity/specificity under clinical endpoints; align data handling and audit trails for HIPAA/GDPR certification.
8. **Edge Hardware Acceleration:** Evaluate NNAPI/GPU/NPU on newer watches to reduce inference latency and enable slightly larger models without extra power draw.

6.6 Risks and Mitigations

- **Data Quality Variance:** Motion artifacts and skin perfusion affect PPG; mitigate with signal-quality indices and auto-rejection before inference.
- **Model Drift:** Physiology changes over time; mitigate with weekly cloud retraining, OTA updates, and optional on-device fine-tuning.
- **Battery Regression:** New features can erode battery life; mitigate with per-feature power budgets, instrumentation, and regression testing on real hardware.
- **Security Exposure:** API misuse or key leakage; mitigate with HMAC auth, key rotation, rate limiting, and end-to-end TLS.

6.7 Summary

The edge-first hybrid architecture proved both feasible and effective: real-time alerts, privacy preservation, competitive accuracy, and acceptable battery life on commodity Wear OS hardware. The remaining gaps—richer sensing, stronger personalization, explainability, and formal clinical validation—define the next phase of work. The system's modular design (separable edge models, cloud training, and OTA delivery) provides a solid foundation for these enhancements.

6.8 Conclusion

This work shows that clinically relevant, real-time health insights are achievable on commodity wearables by pairing edge inference with cloud training and delivery. Compression, activity-aware personalization, and privacy-first design kept latency and power within target while maintaining accuracy above 90%. The architecture is ready to scale to richer sensing, federated learning, and explainability, and it provides a clear path toward regulatory-grade validation without redesigning the stack. The remaining roadmap—broader sensor fusion, adaptive scheduling, and clinical trials—now focuses on depth and trust rather than feasibility.